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Market-wide attention, trading, and stock returns ☆

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A B S T R A C T

Market-wide attention-grabbing events — record levels for the Dow and front-page articles about the stock market — predict the trading behavior of investors and, in turn, market returns. Both aggregate and household-level data reveal that high market-wide attention events lead investors to sell their stock holdings dramatically when the level of the stock market is high. Such aggressive selling has a negative impact on market prices, reducing market returns by 19 basis points on days following attention-grabbing events.

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

Herbert Simon

1. Introduction

Finance models generally assume that investors have unconstrained cognitive resources and at all times are fully active in processing information and making decisions. However, a large body of psychological literature establishes that there are limits to the central cognitive-processing capacity of the human brain.[1] In the real world, many participants, particularly individual investors, can devote only limited attention to their portfolios. Market-wide attention-grabbing events, we hypothesize, cause investors to pay increased attention to their portfolios, thereby increasing trading activity and, in turn, influencing stock prices.

This study's empirical analysis pursues two basic questions: Does market-wide attention affect the trading behavior of investors? Does such attention influence stock market returns? Specifically, we analyze the ability of record-breaking events for the Dow index and front-page articles about the stock market — market-wide attention-grabbing events — to predict trading patterns and market returns. We find that high market-wide attention generates significant trading and price changes.

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

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Measuring a pure attention event presents a challenge, because attention-grabbing events typically coincide with the release of meaningful information. An event well suited for our empirical tests should attract investors' attention while enabling us to control for its economic content. We propose Dow record events and front-page market news events as those fitting these criteria.

As the oldest and most visible market indicator, the Dow Jones Industrial Average attracts heavy media coverage and investor attention when it sets a new record level. We control for the economic information associated with such events by using returns and record events of broader market indexes. Specifically, in addition to Dow record events, we include record events on three other market indexes: the Nasdaq Composite Index, the NYSE Composite Index, and the Standard & Poor's (S&P) 500 Index. To the extent that record events are related to economic fundamentals in a market in which investors fully process all information, we would expect record events of the broader market indexes, the NYSE and the S&P, to show empirical patterns at least as strong as the narrower indexes, the Dow and Nasdaq. Significant empirical patterns emerge only for the latter two indexes, however, consistent with the hypothesis that such patterns reflect the effects of attention attracted by those more visible indexes. The NYSE and the S&P have lower visibility among the four indicators, in that even the Nasdaq appeared nearly 20 times as often as the NYSE and the S&P in the titles of front-page articles in the *New York Times* and the *Los Angeles Times* from 1983 to 2005.

We confirm and generalize our findings using an alternative measure of market-wide attention, namely, prominent media coverage of the stock market. A front-page market news event is defined as an occasion when both the *New York Times* and the *Los Angeles Times* cover the change in the price level of the domestic stock market within front-page articles. In addition to Dow record events, the market news covers many types of events such as market runs, drops, and other indexes hitting new highs. Furthermore, whereas Dow record events happen only when the market price level is high, front-page news events occur during periods with both 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 market-wide attention is pervasive across the entire market. To be specific, we have reached the following two conclusions:

First, Dow record events predict abnormally higher individual-investor selling activities. Front-page market news events exhibit a similar impact when the market index is high. We obtain such empirical results consistently across three independent data sources: individual-investor aggregate order flow from the Institute for the Study of Security Markets (ISSM) and the Trade and Quote database (TAQ) of NYSE, aggregate daily mutual fund flows from Mutual Fund Trim Tabs, and detailed individual trading records from a large brokerage firm provided by Terry Odean. Specifically, we find that following Dow record events or news events when the market index is high, there are higher levels of (i) individual-investor aggregate net selling flow, (ii) flows out of mutual funds, and (iii) selling by households in their brokerage-firm accounts.

Second, Dow record events also predict negative market returns. In our 75-year sample, Dow record events predict the next-day return of the value-weighted NYSE–Amex index to be 19 basis points lower than average. Furthermore, when the Dow first reaches 17 "milestones" (hundred marks when the Dow is below 1,000 and thousand marks when the Dow is over 1,000), the next day sees an additional 28 basis point market drop. When the market is high, front-page news events show a negative predictive ability comparable to that of Dow record events, but news events show little predictive ability when the market index is low. The results imply that aggressive selling places considerable pressure on market prices and lowers next-day returns.

The overall empirical results support the primary mechanism entertained in this study: Market-wide attention events raise the attention level investors pay to their portfolios, causing them to become more active in processing information and making trade decisions. To understand further why active individual investors sell following high market-wide attention, we explore two nonexclusive hypotheses, each of which combines the above-mentioned basic mechanism with a further characterization of how investors trade once their attention level is raised and they become more active. In the first hypothesis, once attention-constrained investors become more active, they trade subject to the "disposition" effect. That is, such investors tend to "sell winners too early and ride losers too long" (Shefrin and Statman, 1985). In the second hypothesis, once attention-constrained investors become more active, they trade to rebalance their portfolios to a desired set of weights. Additional empirical analysis we perform supports both hypotheses.

This study complements the existing literature on investor attention. Barber and Odean (2008) and Da, Engelberg, and Gao (2012) analyze investor attention with a cross-sectional focus, whereas the present study focuses on the variation over time in investors' overall attention level.[2] Barber and Odean (2008) argue that investors face thousands of candidates when they select stocks to buy, but they face relatively few candidates — the stocks they already hold — when they select those to sell. Hence, stock-specific attention-grabbing events have a stronger impact on an investor's allocation of attention across buying candidates than across selling candidates. They find supporting empirical evidence.[3]

[2] Seasholes and Wu (2007) and Huddart, Lang, and Yetman (2009) test the hypothesis of Barber and Odean (2008) with different settings. Hou, Peng, and Xiong (2009) and Li and Yu (2012) analyze the interaction of limited attention and overreaction (underreaction), and find supporting evidence for the impact of attention. Other related studies show that certain types of public information can predict returns on certain types of portfolios. Limited attention seems to be a potentially reliable and natural explanation. See, for example, Huberman and Regev (2001), Hirshleifer, Lim, and Teoh (2004), Hou and Moskowitz (2005), DellaVigna and Pollet (2007, 2009), Hong, Torous, and Valkanov (2007), and Cohen and Frazzini (2008).

[3] Barber and Odean (2008) find that stock-specific attention increases the buying volume of the corresponding stock but has little influence on its selling volume.

Barber and Odean (2008) and Da, Engelberg, and Gao (2012) thus analyze how investors allocate their overall attention across different stocks. This study instead focuses on how investors allocate their attention across time. We find that market-wide events increase the overall level of attention that investors pay to their portfolios.

An additional hypothesis arises from unifying the mechanisms of attention allocation across stocks and across time. When market-wide events increase attention-constrained investors' overall attention level and make them more active, investors are then more likely to face the cross-sectional attention allocation problem described by Barber and Odean (2008). Hence, we should observe that the effects predicted by Barber and Odean (2008) are stronger following high market-wide attention. Consistent with this prediction, we find that the empirical patterns observed by Barber and Odean (2008) are stronger following Dow record events and front-page news events.

The rest of the paper is organized as follows. Section 2 introduces Dow record events and front-page market news events. Section 3 provides the results of the impact of market attention on individual-investor aggregate order flow. Section 4 presents the results of the impact of attention on market returns. Section 5 provides the results on aggregate mutual fund flows. Section 6 reports further analysis for exploring the two hypotheses with individual trading records from a large brokerage firm. Section 7 presents the conclusions.

2. Market-wide attention-grabbing events

2.1. Dow record events

The first type of event that we analyze is a Dow record event, which we define as an occasion when the closing price of the Dow Jones Industrial Average hits a record high.[4] The Dow Jones Industrial Average Index is the oldest continuing market index. It was first published on May 26, 1896, representing the average of 12 stocks from various crucial American industries. The number of stocks increased to 30 in 1928, and has since remained the same.

Dow record events attract heavy media coverage and investor attention due to the widespread use of the Dow. In our hand-collected front-page news data for the sample period from 1983 to 2005, we find that when a specific named index appears in a headline, 92.7% of the time it refers to the Dow Jones Industrial Average Index.

Although the Dow is the most widely used index, it has been criticized for being economically misleading, because it is price-weighted rather than value-weighted, which gives higher-priced stocks more influence over the index than their lower-priced counterparts. Fig. 1 plots the Dow Jones Industrial Average Index from 1928 to 2005. Because of inflation and high equity market returns, the index shows a strong positive trend.

2.2. Front-page market news events

The second type of attention-grabbing event analyzed is a front-page news event, which we define as an occasion 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 individual investors. Unsophisticated investors rely heavily on the public media because they do not have access to as many information channels as professional investors. Thus, media coverage could be the primary mechanism for drawing the attention of individual investors.

Collecting aggregate market news is difficult. Several studies have investigated the impact of security-specific news,[5] using the name or ticker of individual securities as keywords in search engine — a process that does not require intensive manual labor. By contrast, extensive labor is required for collecting market news. First, there are no effective keywords for search engines for this process. To refer to the general stock market, one could use any of a large number of common words, including “shares,” “stock,” “market,” “price,” “Wall Street,” “street,” and “blue-chips.” However, if we were to build a long keyword list including many such commonly used words, although we would obtain numerous pieces of news, many would be unrelated to the stock market. Furthermore, even with a fairly long list of keywords, we would miss many pieces of stock market news that do not contain those keywords, such as “A Happy Birthday for the Bull,” for example.

In this study, news articles on the stock market are 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.

The *New York Times* and the *Los Angeles Times* are selected as the sources for the news data because only the *New York Times*, the *Los Angeles Times*, and the *Wall Street Journal* have been listed consistently in the top five newspapers on the basis of circulation figures from 1983 to 2005. We exclude the *Wall Street Journal* from our analysis because its subscribers are primarily financial professionals, who are less likely to be influenced by the problems of limited attention discussed here.

3. Aggregate NYSE–Amex order flow following attention-grabbing events

In this section, we explore the impact of market-wide attention on the trading behavior of investors, by examining the ability of Dow record events and front-page news events to predict the aggregate order flow of individual investors. We first introduce the aggregate order flow data (Section 3.1), and then investigate the ability of Dow record events (Section 3.2) and market news events (Section 3.3) to predict order flow.

[4] Because of the strong positive trend of the Dow, the index never hits a record low level.

[5] For example, Barber and Odean (2008), Kaniel, Starks, and Vasudevan (2007), and Fang and Peress (2009).

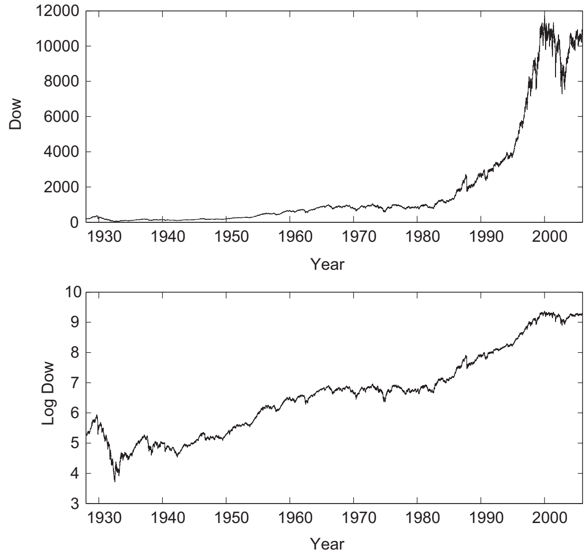

Fig. 1. The Dow Jones Industrial Average Index from 1928 to 2005.

3.1. Data

Following Barber, Odean, and Zhu (2009) and Hvidkjaer (2008), we use small-sized order flow as the proxy for aggregate individual-investor order flow. Aggregate flow is constructed using the tick-by-tick transaction data compiled by the Institute for the Study of Security Markets (ISSM) for the period from 1983 to 1992 and by the New York Stock Exchange (NYSE) for the period from 1993 forward. The latter database is commonly referred to as the Trade and Quote database (TAQ). The combined database contains the quote and trade information for all stocks on the NYSE and the Amex from 1983 onwards.

We identify every trade as buyer- or seller-initiated by 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 to be buyer-initiated if the trade price is above the midpoint of the recent bid–ask quote, and seller-initiated if the trade price is below the midpoint.[6] The ticker rule is adopted if the trade price is on the midpoint. When the ticker rule is applied, a trade is identified to be buyer-initiated if the trade price is above the last executed trading price and seller-initiated if the trade price is below the last executed trade price. A small fraction of trades cannot be identified as buyer- or seller-initiated, namely, those 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 between individual and institutional investors, as outlined by Lee and Radhakrishna (2000). All trades are partitioned into three bins on the basis of trade size. Small trades are defined to be trades of less than \$10,000, which are used as a proxy for trades by individual investors. Large trades are defined to be trades of more than \$50,000, which are used as a proxy for trades by institutional investors. Trades between are classified as medium trades. To adjust for inflation, trade size bins are based on 1991 dollars and adjusted using the Consumer Price Index.

To obtain the daily aggregate order flow for individual and institutional investors, we estimate the sum of the signed trading dollars of all the common stocks listed on the NYSE and the Amex[7] within each trade size bin. We then calculate the daily buyer- and seller-initiated turnover for the three trade size bins by normalizing the buyer- and seller-initiated dollar volume against the lagged market value of the NYSE and the Amex. The aggregate net order flow for each trade size is estimated as the difference between the buyer- and seller-initiated dollar turnover within the corresponding size bin.

Fig. 2 illustrates the seller- and buyer-initiated turnover for small- and large-sized trades from 1983 to 2001. The top and bottom figures on the left are the seller- and buyer-initiated turnovers, respectively, for small trades, and the top and bottom figures on the right are the seller- and buyer-initiated turnovers, respectively, for large trades. Both the buyer- and seller-initiated turnovers for small trades show dramatic increases after the beginning of 2000, whereas the turnovers for large trades remain stable over the entire period. Both Barber, Odean, and Zhu (2009) and Hvidkjaer (2008) indicate that, in recent years, institutional investors have commonly broken down large orders into smaller orders to reduce transaction costs. Because this change causes a fundamental shift in the distribution of trade size and undermines the accuracy of identification of trades initiated by individual and institutional investors, we analyze only the order flow data to the end of 1999. It seems unlikely, however, that such a structural break in the institutional order-flow process coincides with a change in how individual investors respond to attention-grabbing events. In that sense, the analysis can provide insights into the role of attention in the current financial market.

3.2. Aggregate NYSE–Amex order flow following Dow record events

The first basic question pursued by this study is whether market-wide attention affects the trading behavior of investors. Under our hypothesis, since market-wide attention-grabbing events such as Dow records raise the level of attention that constrained investors pay to their portfolios, abnormal trading activities of such investors follow high market-wide attention.

Fig. 3 shows the timing of all Dow record events in the top panel and that of all news events in the bottom panel, from January 1, 1983 to December 31, 1999. During this sample period, there are 469 Dow records (10.9% of trading days) and 683 news events (15.9% of trading days). As expected, the average return on the market (value-weighted NYSE–Amex)

[6] Lee and Ready (1991) indicate that the execution of trades is commonly delayed for a few seconds after an order is submitted. Following their procedure, we use bid and ask quote prices that were in place five seconds before the trade price.

[7] The ISSM and TAQ databases also include quote and trade information for the Nasdaq. However, Nasdaq data are only available from 1987 and many records are missing for a period of six months. Furthermore, the market structure of the Nasdaq differs from those of the NYSE and Amex, which might necessitate a different procedure for identifying the trading directions.

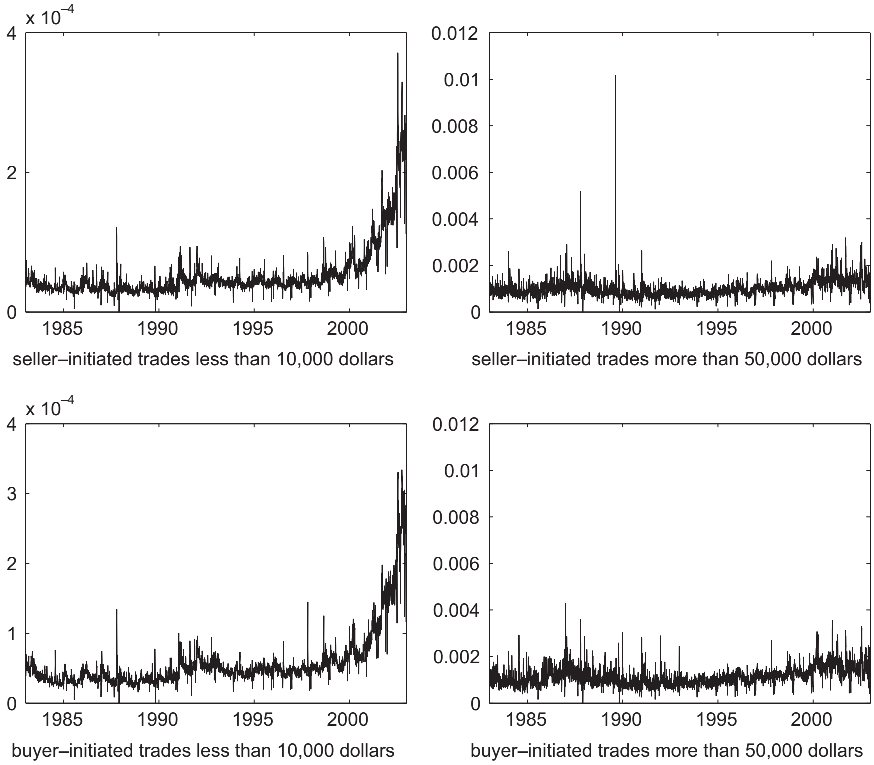

Fig. 2. Buyer- and seller-initiated turnover for small or large trades. The top and bottom figures on the left show the seller- and buyer-initiated turnover (dollar volume normalized by the lag of market value) for small trades on stocks listed in NYSE and Amex. The top and bottom figures on the right are the seller- and buyer-initiated turnovers for large trades on stocks listed in NYSE and Amex. Whereas the turnover for large trades remains stable over the entire sample period, that for small trades shows a positive trend from 2000 onwards.

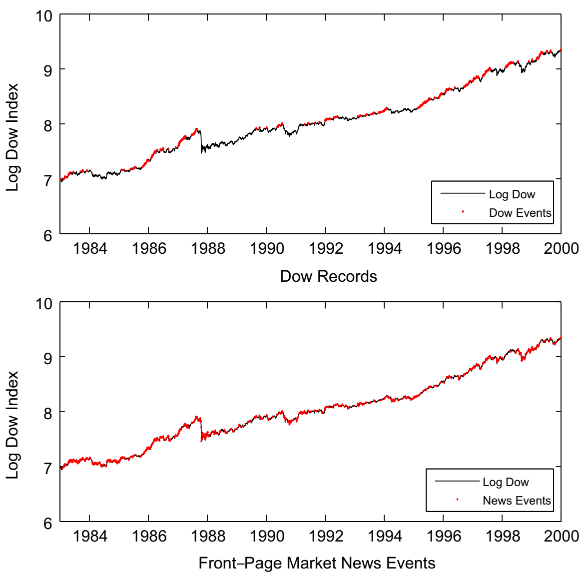

Fig. 3. Dow records and front-page market news events from 1983 to 1999. The top and bottom figures display the time-series distribution of Dow record events and front-page market news events.

on Dow-record days is significantly positive at 0.60%, which is higher than the daily average of the entire sample period (0.06%). The average return on news days is 0.15%, which is similar to the sample average. The average market turnover on both Dow-record and news days is slightly higher than usual: The ratio of turnover on Dow-record (news) days to the average turnover of the past 250 trading days is 114% (114%).

Our news data confirm the anecdotal impressions of heavy media coverage of Dow record events. When the Dow reaches a record level, the probability of both the *New York Times* and *Los Angeles Times* reporting on the stock market in a front-page article is 30.8%, which is twice the frequency on a typical day (15.9%). Furthermore, our news data also confirm that the Dow has the highest visibility across the four indexes — Dow, Nasdaq, S&P, and NYSE. Among the collected news articles, 59.5% mention at least one specific index in the title. Of those articles, 92.7% refer to the Dow, 9.4% refer to Nasdaq, and 0.5% refer to S&P. In the entire sample, only one news item includes the NYSE index in its title. Thus, the indexes that are more economically meaningful (the NYSE and S&P) are less visible.

We analyze the impact of Dow record events 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 net order flow of small-, medium-, or large-sized trades on day $t+1$. The variable, DOW_t, is a dummy variable used to indicate Dow records, that is, when the closing index level of the Dow on day t reaches a new record. Following Chordia and Subrahmanyam (2004), order flow during the previous day (ord_t) and the past one-day and one-year returns on the Dow (ret_t and $ret_{t-250,t}$) are included as control

Table 1
Aggregate daily order flow following Dow record events (1983–1999).

The dependent variables are the order flow of small, medium, and large trades. Trades of less than $10,000 are defined as small trades, trades of more than $50,000 are defined as large trades, and those in between are classified as medium trades. For a given size, the order flow is defined as the buyer-initiated dollar turnover minus the seller-initiated turnover. Finally, the order flow is detrended by the average of the flows over the previous 250 days. The stock universe covers the NYSE and Amex for Panels A and B and excludes Dow stocks in Panel C. DOW_t is dummy variable for Dow record events, which is 1 if the closing level of the Dow Jones Industrial Index hits a record high on day t. NAS_t, NY_t, and SP_t are dummy variables for the record events on the Nasdaq Composite Index, NYSE Composite Index, and S&P 500 Index, respectively. *ret* is the return on the Dow. All variables except the dummy variables are normalized to unit variance. The numbers in parentheses are *t*-statistics estimated using the Newey-West method.

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	−0.057	−0.198	0.516	−0.159	0.068	0.221
	(−2.02)	(−4.91)	(17.60)	(−6.36)	(4.00)	
Medium	0.010	−0.107	0.314	−0.054	0.011	0.076
	(0.32)	(−2.36)	(12.44)	(−1.81)	(0.54)	
Large	0.056	0.149	0.136	0.131	−0.047	0.059
	(1.77)	(2.37)	(2.13)	(5.09)	(−2.12)	

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

	b_1	b_2	b_3	b_4	b_{12}	b_{13}	b_{14}	b_{23}	b_{24}	b_{34}
Small	−0.220	−0.192	0.074	0.077	0.005	−0.056	0.059	0.148	−0.105	−0.060
	(−3.57)	(−3.11)	(0.63)	(0.92)	(0.04)	(−0.39)	(0.46)	(0.84)	(−0.75)	(−0.42)
Medium	−0.190	−0.115	0.180	0.168	−0.082	−0.028	0.140	0.070	0.020	−0.287
	(−2.60)	(−1.90)	(1.18)	(1.50)	(−0.53)	(−0.18)	(0.96)	(0.37)	(0.12)	(−1.83)
Large	0.067	−0.165	0.076	0.171	−0.036	0.011	0.003	0.239	0.012	−0.149
	(0.88)	(−1.02)	(0.71)	(1.67)	(−0.26)	(0.09)	(0.02)	(1.55)	(0.08)	(−1.13)

Panel C: Non-Dow stocks (the same regression specification as Panel B)

	b_1	b_2	b_3	b_4	b_{12}	b_{13}	b_{14}	b_{23}	b_{24}	b_{34}
Small	−0.225	−0.191	0.093	0.074	0.051	0.011	0.004	0.129	−0.106	−0.076
	(−3.58)	(−2.88)	(0.79)	(0.87)	(0.42)	(0.07)	(0.02)	(0.71)	(−0.72)	(−0.55)
Medium	−0.182	−0.111	0.185	0.153	−0.049	−0.001	0.114	0.025	0.030	−0.262
	(−2.50)	(−1.81)	(1.25)	(1.41)	(−0.31)	(−0.01)	(0.78)	(0.14)	(0.19)	(−1.74)
Large	0.030	−0.186	0.136	0.177	0.059	−0.070	0.026	0.143	0.029	−0.140
	(0.43)	(−1.03)	(1.25)	(1.85)	(0.45)	(−0.64)	(0.22)	(1.01)	(0.20)	(−1.13)

variables.[8] This specification controls for the economic information in both short-run and long-run market returns. All series except DOW_t are normalized to have unit variance for ease of interpretation.

Panel A of Table 1 presents the coefficient estimates and t-statistics for the above regression. The results reveal 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. Net selling by individual investors is 19.8% standard deviations higher following Dow record events.

We further control for the economic content of Dow record events by including the record events of the other three indexes: the Nasdaq Composite Index, NYSE Composite Index, and Standard & Poor's 500 Index. This aspect of the analysis is perhaps the key innovation of this paper. The four indexes analyzed are the market indicators that have been used most commonly over the last several decades.[9] As mentioned previously, the NYSE and S&P are broad value-weighted market indexes that contain more economic information than the Dow or Nasdaq, at least in relation to our analysis, in which the aggregate order flow of the NYSE–Amex is the dependent variable. However, as shown by our data on news events, both the NYSE and S&P have low visibility and attract little attention. Even the Nasdaq, which should contain the least relevant economic information for our analysis, because we include none of its stocks, has much higher visibility than the NYSE and S&P. If market-wide attention rather than economic information is the mechanism driving the results, the highly visible indexes (the Dow and Nasdaq) rather than the economically meaningful market indicators (the NYSE and S&P) should show significant predictive ability.

Panel B of Table 1 reports the coefficients and t-statistics for the horse-race test described above, in which we include the record events for the four indexes and their interactions as predictive variables. The Dow shows the strongest negative predictive ability for small-sized order flow (-0.220 with a t-statistic of -3.57). The coefficient on Nasdaq record events is also significantly negative (-0.192 with a t-statistic of -3.11), whereas the NYSE and S&P do not show any significant patterns (0.074 with a t-statistic of 0.63 and 0.077 with a t-statistic of 0.92, respectively).

That NYSE record events have no predictive ability for NYSE stocks, whereas record events on both the Dow and Nasdaq have strong predictive ability, suggests that high market-wide attention, not economic information, drives the abnormal net-selling behavior of individual investors. This conclusion does not require that the NYSE composite index completely covers the economic information in the Dow. In other words, our empirical conclusion is valid if the Dow contains unique information. To predict the aggregate order flow of the entire stock market, the real market index (the value-weighted NYSE composite index) should contain at least the same level of economic content as the Dow. It is rather striking that NYSE records show no significant relation to aggregate small-sized order flow, and this result suggests that economic information is not the primary driver of our results.

Next, we conduct a "contagion" test for impacts of Dow records on the order flow of non-Dow stocks.[10] If the predictive ability of Dow records is primarily driven through the attention channel, then Dow records, which draw attention across the entire market, should predict the individual-investor order flow of both Dow stocks and non-Dow stocks. By contrast, if economic information is the primary channel, the ability of Dow records to predict the order flow of non-Dow stocks should be weak. Panel C of Table 1 reports results with the dependent variable defined as the market order flow excluding firms in the Dow. The empirical results are essentially the same as those in Panel B, for which the order flow of all firms is the dependent variable. Dow records show a strong ability to predict the small-sized order flow excluding that of Dow firms, whereas NYSE records again exhibit no ability to do so. These results provide solid support for the influence of market attention on the trading activities of individual investors.

In all of the above tests, Dow records also show some ability to predict the middle-sized order flow, but with smaller economic magnitudes. Because the middle-sized order flow contains a portion of individual-investor trading activities, the consistent empirical patterns support the influence of attention on individual investors. Dow record events do not seem to have an influence on the trading of institutional investors — large-sized order flow. Despite some patterns in Panel A, the significant predictive ability disappears in Panels B and C.

In the above empirical analysis, we use the same set of control variables: order flow of the previous day, market return of the previous day, and market return of the previous year. The empirical conclusions are robust across the following specifications with different control variables: (i) with more past market returns as additional control variables (i.e., adding the market returns of the previous week and the previous month to the regressions), (ii) with lagged market returns of different indexes as control variables (i.e., replacing the returns of the Dow with the returns of the NYSE or NYSE–Amex), (iii) with lagged market turnover as an additional control variable, and (iv) with nonlinear functions of past returns as additional control variables (i.e., adding quadratic terms for past market returns or dummy variables for extreme past returns). All of these results can be provided upon request.

In unreported results, we explore the predictive ability of record events of a similar but unobservable index, "Dow3," which includes only the three stocks with the highest weights in the Dow. According to our attention hypothesis, investors' attention can be drawn only by record events of the real Dow. Although the Dow3 could contain independent

[8] The returns on the Dow may capture more information overlapping with Dow records. An alternative is the return on the NYSE–Amex, which may capture more economic information for the entire market, particularly because the dependent variable is the order flow of all the stocks listed on the NYSE and Amex. The correlation between the returns on the Dow and NYSE–Amex is 94%, and the empirical patterns are virtually the same with returns on the NYSE–Amex used as control variables.

[9] 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, to reflect the value of all stocks traded on the exchange. The S&P 500 Index was introduced on March 4, 1957, and comprises the stocks of 500 large-cap corporations.

[10] We thank the referee for this suggestion.

Table 2
Aggregate daily order flow following front-page market news events (1983–1999).

The dependent variables are the order flow of small, medium, and large trades. Trades of less than $10,000 are defined as small trades, trades of more than $50,000 are defined as large trades, and those in between are classified as medium trades. For a given size, the order flow is defined as the buyer-initiated dollar turnover minus the seller-initiated turnover of the NYSE–Amex. Finally, the order flow is detrended by the average of the flows over the previous 250 days. $News_t$ is the news dummy variable, 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 variable, which is 1 if the closing NYSE–Amex index level on day t falls into the top 10% quantile for the previous 500 days. DOW_t is dummy variable for Dow record events. *ret* is the return of the value-weighted NYSE–Amex index. All variables except the dummies are normalized to unit variance. The numbers in parentheses are t-statistics estimated using the Newey-West method.

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

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

	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)	

economic information, this unreported index should have no influence beyond the real Dow. In the regression with records of both the Dow and Dow3, Dow records show essentially the same ability to predict small-sized order flow, whereas Dow3 records show no significant ability, consistent with our attention hypothesis.

We also analyze “ice-breaking” record events, defined as records not preceded by other record events in the last month. Such events might attract more attention and have larger influence on individual trading. The results show that ice-breaking records predict a greater negative small-sized order flow than do standard Dow records, but the difference between ice-breaking and standard Dow records is not statistically significant, perhaps due to the low number of ice-breaking record events. In the sample period, there are 44 ice-breaking records (9.1% of all Dow records). We further explore ice-breaking record events with various lengths of time from the previous record. In other words, ice-breaking record events are defined as records that not preceded by other record events in the previous 2, 5, 10, 30, and 90 days. Because record events with longer intervals likely draw more market attention, we expect those events to exert a stronger impact. Such a pattern appears to exist. The coefficients of ice-breaking records are monotonically declining with increasing interval length, although none are individually statistically significant. Hence, the impact of ice-breaking records — forecasting additional net selling flow — increases with the length of time from the previous record.

To summarize, we find a strong impact of market-wide attention on the trading behavior of individual investors. Dow record events predict abnormal net selling flow of individual investors in aggregate. We further show that such a pattern exists only for the highly visible indexes, the Dow and Nasdaq, and does not hold for the more economically meaningful indexes, the NYSE and S&P. These results suggest that pure attention, rather than economic information, drives our findings. The above results provide strong support for the primary mechanism in this study: Market-wide attention-grabbing events raise the attention level investors pay to their portfolios, causing them to become more active in processing information and making trade decisions. To understand further why activated individual investors sell, we provide additional analysis and discussion in Section 6.

3.3. Aggregate NYSE–Amex order flow following front-page market news events

In this subsection, we analyze the ability of another type of market-wide attention-grabbing events — front-page market news events — to predict aggregate order flow. Given that these events are less specific in nature than Dow record events, the findings relate to a broader setting in the following sense. First, stock market news covers diverse topics, such as rises and falls in the market, and other indexes hitting records. Second, unlike Dow record events, which occur only when the market index is high, front-page news events occur during both good and bad economic periods, as shown in Fig. 3.

Given that activated investors may trade differently in good and bad periods, we define a dummy variable for time periods with high index levels, D_t^G, which 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, and equals zero otherwise.[11] We refer to such

[11] The empirical results are robust across different quantiles (5%, 10%, and 15%) and lengths of time (one, two, and three years).

Table 3
Next-day market returns following attention-grabbing events.

The dependent variable is the next-day percent return on the value-weighted NYSE–Amex index, except in Regression (6). The dependent variable in (6) is the return of the index, which excludes Dow stocks. DOW_t, NY_t, NAS_t, and SP_t are dummy variables for the record events of the Dow Jones Industrial Average Index, Nasdaq Composite Index, NYSE Composite Index, and S&P 500 Index, respectively. $Milestone_t$ is dummy variable for the milestone event, which is 1 if the Dow breaks one hundred marks (when the Dow is below 1,000) or one 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 for the previous 500 days. V_t is the detrended dollar turnover of the NYSE–Amex. V_t is normalized to unit variance. The numbers in parentheses are t-statistics estimated using the Newey-West method.

Regression	(1) 1974–2005	(2) 1931–2005	(3) 1931–1970	(4) 1971–2005	(5) 1931–2005	(6) 1931–2005 Non-Dow	(7) 1983–2005	(8) 1983–2005
DOW_t	−0.284	−0.193	−0.123	−0.225	−0.163	−0.187		−0.192
	(−5.07)	(−4.73)	(−2.40)	(−4.13)	(−4.23)	(−4.68)		(−3.75)
$News_t$							0.088	0.088
							(0.93)	(1.08)
D_t^G							−0.008	0.004
							(−0.34)	(0.14)
$News_t \times D_t^G$							−0.238	−0.205
							(−2.17)	(−2.09)
NAS_t	−0.075							−0.102
	(−1.76)							(−2.21)
NY_t	−0.041							−0.022
	(−0.54)							(−0.29)
SP_t	0.122	0.013	0.056	−0.014	0.004	0.016		0.133
	(1.40)	(0.45)	(1.72)	(−0.32)	(0.14)	(0.55)		(1.58)
$Milestone_t$					−0.277			
					(−2.67)			
ret_t	0.114	0.118	0.100	0.135	0.118	0.138	0.082	0.083
	(6.87)	(9.60)	(5.74)	(9.63)	(9.60)	(11.13)	(4.05)	(3.86)
V_t	0.008	0.008	0.009	0.007	0.008	0.031	−0.000	0.006
	(0.65)	(0.59)	(0.31)	(0.57)	(0.59)	(1.83)	(−0.01)	(0.27)
$ret_t \times V_t$	−0.013	−0.006	−0.004	−0.015	−0.006	−0.013	−0.010	−0.009
	(−4.01)	(−0.93)	(−0.35)	(−4.22)	(−0.93)	(−1.28)	(−3.06)	(−1.48)
Constant	0.061	0.049	0.053	0.045	0.049	0.033	0.050	0.060
	(5.45)	(6.82)	(4.99)	(4.44)	(6.82)	(4.29)	(2.49)	(2.95)
R^2	0.012	0.013	0.013	0.015	0.014	0.016	0.007	0.006

periods as "good times." For the sample, between 1983 and 1999, 58.9% of the trading days and 51.0% of the news events occur in good times.

We analyze the predictive ability of front-page news events according to the following regression:

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

where the dependent variable is the aggregate order flow, and $News_t$ is the dummy variable for front-page market news events.[12] The terms ret_t and $ret_{t-250,t}$ are the past one-day and one-year returns on NYSE–Amex. The coefficient on $News_t$, β_1, shows the predictive ability of front-page news in bad times, and β_{12} is the difference between the predictive abilities of news in good and bad times.[13]

Panel A of Table 2 presents the results of the above regression. First, similar to Dow record events, front-page news events that occur in good times strongly predict abnormal selling flow. Thus, front-page market news — general attention to the market — triggers abnormal selling by individual investors when the index level is high. The coefficient for front-page news events in good times, $\beta_1 + \beta_{12}$, is -0.216 with a t-statistic of -3.88. The magnitude is also economically significant: Individual-investor net selling is 21.6% standard deviations higher following news events that occur in good times. Moreover, news events also show negative predictive ability for medium-sized trades, which should include a significant portion of individual trades. $\beta_1 + \beta_{12}$ is -0.170, with a t-statistic of -2.71.

Front-page market news events also appear to show some predictive ability for individual-investor buying flow during bad times. For small-sized order flow, the coefficient for news events during bad times, β_1, is 0.183 with a t-statistic of 2.17. However, the predictive ability for medium-sized trades disappears when the market index is low.

Panel B of Table 2 presents the results in the regressions including front-page news events and Dow record events as dependent variables together. The magnitudes of the coefficients on news events and Dow events are similar to those in regressions treating the two sets of events separately. General market attention — front-page market news events — seems to capture different dimensions of

[12] In the empirical test described in this subsection, day t begins at the opening time of the stock market and ends at the opening time on the next calendar day. Hence, $News_t$ is published in the morning of the same calendar day as that of ord_{t+1}.

[13] Studies suggest that some news contains new information and thus has an impact on future prices, e.g., Huberman and Regev (2001), and Tetlock (2007, 2011). It appears unlikely that the news articles in this study contain such information, because most mainly repeat highly visible public information (e.g., the closing level of the Dow and the trading volume of the previous trading day).

attention from Dow record events and demonstrate independent predictive ability for aggregate order flow.

The results for front-page market news events confirm our findings for Dow record events: High market-wide attention predicts exceptional selling by individual investors when prices are high. The overall results in this section provide an affirmative answer to our first basic question. Market attention strongly influences the trading behavior of individual investors.

4. Market returns following attention-grabbing events

The second basic question pursued by this study is whether market attention influences stock market returns. The previous section demonstrates that high attention strongly influences individual-investor trading behavior. In particular, high attention triggers abnormal individual-investor selling when the market index is high, and, to a lesser degree triggers individual buying when the market index is low. The abnormal trading of individual investors could affect market prices and produce a relation between market attention and future market returns. In this section, we investigate this possibility. We find that high attention demonstrates strong negative predictive ability for next-day returns when the market index is high but demonstrates little predictive ability when the market index is low.

Specifically, Dow record events predict a lower next-day return on the value-weighted NYSE–Amex index. Front-page market news events have a similarly negative predictive ability when the index is high, but they have no significant predictive ability when the index is low. Thus, market attention affects the aggregate price level when individual investors sell stock aggressively following attention-grabbing events.

Table 3 presents the ability of attention-grabbing events to predict daily returns on the value-weighted NYSE–Amex index. Following Gervais, Kaniel, and Mingelgrin (2001) and Llorente, Michaely, Saar, and Wang (2002), we include the lag of market return and trading volume on the NYSE–Amex, and their interaction as control variables.

Regression 1 presents the results of regressing market returns on the record events for the four indexes and control variables. The sample period begins in 1974, three years after the introduction of the Nasdaq, the youngest of the four indexes was introduced. Dow record events predict a next-day return at 28.4 basis points lower with a t-statistic of -5.07. Another visible index, Nasdaq, predicts a next-day return at 7.5 basis points lower, which is significant using a one-sided t-test. This result is particularly impressive, since no stocks listed on Nasdaq are included in this analysis. However, the coefficients for the NYSE and S&P do not differ significantly from zero. Consistent with the empirical findings of the previous section, we find that the visible indexes (Dow and Nasdaq) show a significantly predictive ability, whereas the economically meaningful indexes (NYSE and S&P) exhibit no ability. Hence, it is pure market-wide attention rather than economic information that produces strong impact on market returns.

The above pattern also holds in a long sample period. Regression 2 presents the results for the record events of the Dow and S&P for a sample period from 1931 to 2005. Apart from the Dow Jones Industrial Average Index, the only index with a long history in the US is Standard & Poor's Composite Index, which was introduced in January 1928 and included 90 stocks until 1957.[14] On March 4, 1957, the S&P was extended to comprise a total of 500 stocks. In the long sample period, Dow record events predict a next-day return at 19.3 basis points lower with a t-statistic of -4.73, whereas the coefficient on the S&P — the less visible index — is only 1.3 basis points with a t-statistic of 0.45. Regressions 3 and 4 present the results of record events on the Dow and S&P for the analysis of two subsamples. The results are consistent with the findings for the entire sample.

Next, we analyze an interesting attention-grabbing event, namely a “milestone event.” A milestone event is defined as an instance of the closing level of the Dow breaking one hundred marks (when the level of the Dow is below 1,000) or one thousand marks (when the level of 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, because the impact of reaching a hundred or a thousand marks should be purely psychological. Compared with Dow record events and news events, milestone events are rare. Even in the 75-year sample from 1931 to 2005, only 17 milestone events are observed.

Regression 5 presents the results obtained using dummy variable for such events — $Milestone_t$ — as an additional regressor. The slope of $Milestone_t$, 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 those in Regression 2. This result provides further support for the pure attention argument. Milestone events, which grab even more investor attention than standard Dow record events, have a greater effect on price levels than standard Dow record events. Market returns are 46.4 basis points lower after milestone events. In unreported results, we also analyze the milestone events for the less visible index — the S&P Composite Index, and we find that its coefficient is not statistically or economically significant at all. In addition, we investigate the impact of Dow milestone events on small-sized order flow and obtain consistent but insignificant results because there are so few milestone events during the relatively short sample period.

Regression 6 provides results for the contagion test, which analyzes the influence of Dow records on non-Dow returns. The dependent variable is defined as the market return excluding firms in the Dow. As discussed in the previous section, Dow records, attracting attention across the entire market, should have a similar influence on non-Dow stocks

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

and Dow stocks. The results support the attention hypothesis. For the sample period from 1931 to 2005, following Dow records, the next-day market return excluding Dow firms is 18.7 basis points lower. The influence is essentially the same as that on the market return including Dow firms.[15]

Finally, we explore the ability of front-page news events to predict market returns. Regression 7 reports results of the regressions of next-day returns on news events, the dummy variables of good times, and their interaction. The coefficient on $News_t$ — the predictive ability of front-page news events in bad times — is 0.088, which is not significantly different from zero. News events appear to show little predictive ability when the market index is low. The coefficient on $News_t \times D_t^G$ — the difference between good and bad times — is significantly negative (-0.238 with a t-statistic of -2.17). The sum of these coefficients — the predictive ability of front-page news events in good times — is -0.150 with a t-statistic of -2.70. The market returns are 15.0 basis points lower following news events when the market index is high. In addition, we also check the predictive ability of Dow records and front-page market news in a multiple regression (Regression 8). The coefficients on news events and Dow events are similar in magnitude to those in regressions treating the two sets of events separately.

The empirical results imply that selling by individual investors causes negative market returns. Such results are consistent with the studies of Barber, Odean, and Zhu (2009) and Hvidkjaer (2008), which find that individual-investor trading influences stock returns. Furthermore, the stronger influence of individual investors on returns during good times is consistent with several recent studies that find that the anomalies are stronger during such periods (Cooper, Gutierrez, and Hameed, 2004; Stambaugh, Yu, and Yuan, 2012). These studies in general argue that their findings are partly caused by the time-varying influence of individual investors (or noise traders). Individual investors participate in the market more aggressively due to optimism or sentiment during good times while many of them "exit" the stock market during bad times due to their reluctance to take short positions. Overall, our results suggest a similar time-varying pattern of the impact of market attention on stock market returns.

We also explore the robustness of return predictability. In the above analysis, we include the lagged 1-day return, the lagged 1-day turnover, and their interaction in the regressions. The results are essentially the same in the following specifications: (i) with the lagged 1-day return as the only control variable, (ii) with more lagged returns as additional control variables, and (iii) replacing the dependent variable with the market return that excludes the 20% of stocks with the lowest trading dollar values. The third specification minimizes the influence of non-trading stocks on our analysis. In addition, the positive autocorrelation of market returns does not influence attention impact. The coefficients for Dow and news are not sensitive to lagged return being included as a control variable.

In general, the negative impact on market returns persists for more than one day. For example, for the sample from 1974 to 2005, Dow record events predict that the cumulative market returns of the following three days are 44.3 basis points lower with a t-statistic of -5.07. In this specification, the lagged 3-day cumulative return instead of the lagged 1-day return is used as the control variable. Furthermore, we also check whether the record events forecast a price reversal that follows the price slide of the first few days. The slope is positive, which is consistent with a reversal, but it is not statistically significant. The insignificance may be attributed to an increase in noise as the period of cumulative returns is extended, or the seeming reversal does not in fact exist.

The overall results in this section provide an affirmative answer to our second basic question: Market attention influences stock market returns, in a way that is consistent with its impact on individual-investor trading. High attention shows strong negative predictive ability for future returns when the market index is high.

5. Aggregate mutual fund flow

In Section 3, we investigate individual-investor trading activities using aggregate order flow data from the stock market. Since the empirical findings show that the effect of heightened market attention on trading stocks is pervasive, we explore whether attention-grabbing events also affect the buying and redeeming of shares in mutual funds.

In fact, the analysis of mutual funds could be of particular relevance to this study. First, both conventional wisdom and formal theoretical models suggest that unsophisticated attention-constrained investors are more likely to choose mutual funds as investment vehicles.[16] Second, although for the aggregate order flow data, we must use trade size as a proxy for trader identities — individual or institutional investors — the risk of mismeasurement is low for mutual fund flow data, because individual investors hold approximately 90% of total assets in mutual funds.[17]

Using the flow data for mutual funds, we obtain empirical results that are consistent with the findings obtained using the aggregate order flow. We find strong empirical evidence for that high market attention causes individual investors to redeem shares in mutual funds when the market index is high, and find relatively weak evidence for that they buy shares when the market index is low.

[15] After the financial crash, the Dow Jones Industrial Average Index did not reach a new record until 2013. In the analysis of data including the records events in 2013, the empirical patterns documented in this section are essentially the same.

[16] For example, 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 an allocation of attention across different types of information would make mutual funds more attractive to attention-constrained investors.

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

Table 4
Aggregate daily mutual fund flow following attention-grabbing events (1998–2005).

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 dummy variables for the record events of the four indexes. $News_t$ is news dummy variable, 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 value of the NYSE–Amex index level falls into the top 10% quantile within the previous 500 days. $Flow_{t\text{-}i}$ is the lagged mutual fund flow and eight lags of the flow are included in the regressions. To save space, only the coefficients on the first two lags are reported in the table. Regression (2) includes the interactions of the four dummy variables, but the coefficients of these interactions are not reported here. All variables except the dummies are normalized to unit variance. The numbers in parentheses are *t*-statistics estimated using the Newey-West method.

Regression	(1)	(2)	(3)	(4)
DOW_t	−0.344	−0.553		−0.300
	(−2.70)	(−3.21)		(−2.28)
$News_t$			0.220	0.226
			(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	−0.172
	(−4.47)	(−4.06)	(−4.66)	(−4.48)
$Flow_{t-1}$	−0.092	−0.078	−0.091	−0.087
	(−2.78)	(−2.35)	(−2.80)	(−2.65)
ret_t	−0.077	−0.080	−0.074	−0.070
	(−2.34)	(−2.42)	(−2.25)	(−2.17)
$ret_{t-250,t}$	0.060	0.069	0.069	0.069
	(2.76)	(2.85)	(2.77)	(2.72)
Constant	−0.007	0.012	−0.022	−0.021
	(−0.29)	(0.46)	(−0.79)	(−0.77)
R^2	0.109	0.121	0.111	0.114

5.1. Data

The daily mutual fund flow data are 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 data from the same source, but for a shorter sample period, and show that the Trim Tabs data contain 16.5% (20%) of all U.S. equity mutual funds by number of funds (by net assets).

The mutual fund flow of Trim Tabs is calculated using net asset value (NAV), which is publicly available, and total asset value, which is received privately by Trim Tabs on the morning of the next day. Despite the obvious accuracy of NAV, obtaining information on total asset value is delayed by 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. As a consequence of the delay, the daily aggregate mutual fund data comprise two-day average series. The aggregate flow on day $t+2$ includes the flows of some funds on day $t+2$ and the flows of the other funds on day $t+1$. To address this issue in our predictive regressions, the attention-grabbing event at day t is used to predict the combined flow of days $t+1$ and $t+2$.

5.2. Empirical results

Table 4 presents the regressions of aggregate fund flow on attention-grabbing events, lags of market returns, and lags of fund flow. Following Edelen and Warner (2001), we include eight lags of fund flow as control variables. The empirical patterns below are unaffected by the choice of lag number. To better understand economic magnitude, all the variables except the dummy variables are normalized to unit variance.

Consistent with the results obtained using the aggregate order flow data, we find that individual investors also redeem more mutual fund shares following Dow record events. Regression 2 reports results for the record events of the four market indexes. The coefficient on Dow events is −0.553 with a *t*-statistic of −3.21. The net outflow from mutual funds is 55.3% standard deviations higher following Dow record events. For the total assets in equity mutual funds in 1999 — $4.04 trillion according to the Investment Company Institute — this estimate implies that net outflow is $2.3 billion higher on days following a Dow record. For Nasdaq record events, the net flow is 35.1% standard deviations higher. However, neither of the coefficients for the economically meaningful indexes, the NYSE or S&P, is significantly different from zero. Similar to the findings in the last two sections, the evidence suggests that increased market attention rather than economic information is the driving force.

In Regression 3, we find consistent evidence for attention effects of front-page market news events. News shows significant predictive ability in both good and bad times. The coefficient on news — the effect of front-page news in bad times — 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 — the effect of front-page news in good times — is -0.304 and is statistically significant. Thus, net outflow is 30.4% higher following front-page market news events that occur in good times. Regression 4 reports the results with news and Dow records in the joint test. The magnitude and significance remain essentially the same for most of the estimates, indicating that both front-page news and Dow events have a strong influence on mutual fund flow.

In summary, we find empirical results consistent with those obtained using aggregate order flow: Individual investors redeem their shares in mutual funds following attention-grabbing events when the market index is high, and they modestly increase their fund holdings following attention-grabbing events that occur when the market index is low. Hence, high attention influences not only individual investors who trade individual stocks, but also those who invest in mutual funds.

6. Individual-investor transactions

In the previous sections, we show several sets of empirical results which demonstrate the pervasive impact of pure market attention. We find particularly strong evidence that, following market-wide attention, individual investors sell stocks and redeem shares in mutual funds when the market level is high. The aggressive selling of investors causes market returns to drop. In this section, using detailed transaction records from a large brokerage firm, we explore beyond the primary mechanism of this study, by discussing why activated individual investors sell following Dow record events and news when the market index is high (Sections 6.1 and 6.2). In addition, we propose and analyze a hypothesis unifying the market-wide attention in this paper and the stock-specific attention in Barber and Odean (2008) (Section 6.3).

6.1. Disposition effect and rebalance needs

The primary mechanism in this study is that market-wide attention-grabbing events raise the overall levels of attention that investors pay to their portfolios, which leads investors to be more active in processing information and making trade decisions. In this section, we propose two hypotheses, each of which combines this basic mechanism with a further characterization of how investors trade once they become more active.

In the first hypothesis, once attention-constrained investors become more active, they trade subject to the "disposition" effect. That is, such investors tend to "sell winners too early and ride losers too long" (Shefrin and Statman, 1985). Shefrin and Statman (1985) and Odean (1998) define a stock as a winner (loser) for an investor if the current price of this stock is higher (lower) than its average purchase price of this investor. The disposition effect is one of the most robustly documented behavioral biases of individual investors.[18] After high market-wide attention makes such investors more active, they are more likely to sell winner stocks in their portfolio to lock in gains, while keeping their positions in loser stocks intact. In the case of Dow record events, which make these attention-constrained investors more active, they are likely to notice that many of their stocks are winners and sell these winner stocks.

In the second hypothesis, once attention-constrained investors become more active, they trade to rebalance their portfolios to a desired set of weights. These investors have desired weights across individual stocks and other types of investment, such as bonds, and they try to restore the relative weights of their investments. After high market events make such investors more active, they are likely to sell (buy) those stocks that have positive (negative) returns since they last rebalanced, in order to restore the relative weights to their target levels. Following Dow record events, these attention-constrained investors notice that many of their stocks have positive returns since they last rebalanced their portfolios, and they sell these stocks.

These two hypotheses are not mutually exclusive. Once market attention makes investors more active, some could trade subject to the disposition effect and some could trade to rebalance. Furthermore, there could also be a significant number of attention-constrained investors who trade with idiosyncratic motivations. However, as long as these idiosyncratic motivations have no systematic direction, the trades that are motivated in one direction should be balanced by trades motivated in the opposite sense.

The empirical results of individual-investor aggregate order flow and aggregate mutual fund flow are consistent with both hypotheses. When the market index level is high, portfolios of investors include plenty of winner stocks and stocks with recent positive returns. Both hypotheses suggest that activated individual investors should sell or redeem shares following heightened attention in good times. With the detailed transaction records in this section, we provide more analysis on the two hypotheses.

6.2. Empirical results

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

We build stock-level holdings data for all the investors in the sample. Each observation represents a stock in the

[18] In addition to Shefrin and Statman (1985), many other studies show that individual investors are subject to disposition effects. See, for example, Odean (1998), Grinblatt and Keloharju (2001), and Seru, Shumway, and Stoffman (2010).

[19] If a household is both active and affluent, it is labeled as active. The patterns obtained from the empirical analysis are weaker but significant if we include active traders in the sample.

Table 5
Individual-investor selling decisions following record events and news events (1991–1996).

This table reports the coefficients and t-statistics of the logistic regressions. The dependent variable is $Sell_{i,j,t+1}$, which is 1 if stock i is sold by investor j at time $t+1$, and 0 otherwise. DOW_t, NAS_t, NY_t, and SP_t represent the record events of the Dow Jones Industrial Average Index, Nasdaq Composite Index, NYSE Composite Index, and S&P 500 Index, respectively. $News_t$ is 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 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 positive return dummy, which is 1 if the return of stock i from the previous 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 parentheses are t-statistics estimated using the standard method, and the numbers in brackets are t-statistics estimated clustering the residuals on the same day.

								$D^{Win}_{i,j,t+1}\times$					$D^{Pos}_{i,j,t+1}\times$				
	DOW_t	NAS_t	NY_t	SP_t	$News_t$	$D^{Win}_{i,j,t+1}$	$D^{Pos}_{i,j,t+1}$	DOW_t	NAS_t	NY_t	SP_t	$News_t$	DOW_t	NAS_t	NY_t	SP_t	$News_t$
(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)	0.041	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]	
(3)					0.206												
					(29.39)												
					[5.36]												
(4)					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]

portfolio of a single investor on a given day. We examine the selling activities of individual households, by constructing the dependent variable $Sell_{i,j,t+1}$, which equals one if investor i sells stock j on day $t+1$, and zero otherwise.

Using the detailed trading records of individual investors, we estimate investors' purchasing prices and returns from the previous time at which investors trade. In particular, to identify a winner stock empirically for the disposition effect, following Odean (1998), we use the average purchase price as the proxy for the reference point. 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 of investor j on day $t+1$.[20] We also define $D^{Pos}_{i,j,t+1}$, which is 1 if the cumulative return of stock i from the previous time at which investor j trades is positive.

Specifically, we examine the following logistic regression:

$$\begin{aligned} logit(Sell_{i,j,t+1}) = a + b\ X_t + c\ D^{Win}_{i,j,t+1} + d\ D^{Pos}_{i,j,t+1} \\ + e\ X_t D^{Win}_{i,j,t+1} + f\ X_t D^{Pos}_{i,j,t+1} \\ + g_1\ ret_{j,t} + g_2\ ret_{j,t-250,t} \\ + h_1\ ret_t + h_2\ ret_{t-250,t}. \end{aligned}$$

X_t is the dummy variable for Dow record events or front-page market news events. The lagged short- and long-run returns of this stock and the value-weighted market index are included as control variables.

If many active investors sell winner stocks, the coefficient for the interaction between the attention dummy variable and winner dummy variable, e, should be positive. That is, the impact of attention is stronger for winner stocks. If many active investors sell stocks with positive returns, the coefficient for the interaction between the attention dummy variable and positive return dummy variable, f, should be positive. A positive estimate of f supports the rebalancing hypothesis. However, if rebalancing is only one of the reasons why these investors trade, $D^{Pos}_{i,j,t+1}$ could be a noisy empirical measure for rebalancing needs, because these investors may not adjust positions fully to their desired weights in their previous transactions. In such a scenario, $D^{Win}_{i,j,t+1}$ may also capture rebalancing needs at some level.

In Table 5, we first investigate the impact of increased attention on general stocks in the setting without winner and positive dummies in Regressions 1 and 3. We find the results consistent with those using the aggregate individual-investor order flow — high market attention increases the selling probability of general stocks. In Regression 1, Dow and Nasdaq record events raise the probability of selling stocks by 13.9% and 18.5%, respectively. Both slopes are statistically significant. Consistent with the crucial role of pure attention, the NYSE and S&P show no significant patterns. In Regression 3, front-page market news events show the impact of a similar economic magnitude. To address the concern of correlated residuals, in addition to the t-statistic obtained using the standard procedure, we also report the t-statistic obtained using the clustered standard deviation, which allows the residuals on the same day to be correlated.

The main empirical results are reported in Regressions 2 and 4. With winner and positive dummies in the regression, the coefficient on Dow record events is 0.041, and the coefficient on the interaction between Dow events and the winner dummy is 0.105, which is significant with both procedures to estimate standard deviation. Thus, whereas Dow record events increase the probability of selling a general stock by a moderate magnitude (4.1%), the impact is tripled for winner stocks (14.6%=4.1%+10.5%). The coefficient on the interaction of Dow and the positive dummy is 0.028, which is not significant. It seems that the effect of attention on the stocks with positive returns is not significantly stronger. For the Nasdaq record event, its interactions with winner and positive dummies are both significant, which lends some support to both hypotheses. Regression 4 presents the results of front-page news events. The impact of news events is doubled for winner stocks relative to general stocks but there is no significant additional impact on stocks with positive returns.

We find although the market attention raises the selling possibilities for all stocks, the impact is stronger for winner stocks, which may be driven by the disposition effect and rebalancing needs. Overall, the above empirical results support both hypotheses.

6.3. Unifying attention impact across stocks and across time

Barber and Odean (2008) analyze attention impact with a cross-sectional focus — attention allocation of investors across different securities. This study explores the attention allocation of investors through time. In this subsection, we test a unifying hypothesis: When market-wide events increase the overall attention levels of attention-constrained investors and make them more active, such investors are then more likely to face the problem of cross-sectional attention allocation described by Barber and Odean (2008). Thus, following Dow record events and news events, we expect to observe stronger empirical patterns of Barber and Odean (2008). As shown below, we find empirical results that are consistent with this hypothesis.

The key argument of Barber and Odean (2008) is as follows. Attention-constrained investors choose candidate stocks from several thousand stocks when they want to buy, but select candidates from few stocks that they already hold when they want to sell. Hence, the effect of stock-specific attention in the cross-section should be stronger in buying activities than in selling activities. In other words, in the cross-section, attention-grabbing stocks are likely to attract potential buyers but have little effect on potential sellers. Using the abnormal trading volume and returns of individual stocks as a proxy for stock-specific attention, Barber and Odean find significant net buying order flows for the stocks with high attention and significant net selling flows for stocks with low attention.

In the unifying hypothesis, following heightened market-wide attention, the attention impact in the cross-section should be stronger. Specifically, there should be a wider spread among the net order flows between stocks

[20] For those observations in which a sale takes place, to identify a winner we compare the selling price with the average purchase price. For the remainder of the observations, in which no sale is executed, we compare the closing price on the day with the average purchase price.

Table 6
Buy–sell imbalance for stocks sorted on the abnormal trading volume.

Buy–sell imbalances are reported for the trades of investors at a large discount brokerage (from January 1991 to November 1996). Stocks are sorted into deciles on the basis on the current day's abnormal volume. The decile of the highest abnormal volume is split into two (10a and 10b). Abnormal volume is calculated as the ratio of the current day's volume divided by the average volume over the previous 250 trading days. We calculate the number (value) imbalance as the number (value) ratio of the purchase minus the number (value) ratio of the sales divided by the total number (value) ratio of trades. The table reports the mean of the time-series of daily imbalances, for the entire sample period, for the days following those with market returns close to the average market return of Dow records, for the days following Dow records, for the days following front-page market news, and for other days. The numbers in parentheses are *t*-statistics.

	All days		Following days with similar returns as Dow records		Following Dow records		Other days		Following front-page market news		Other days	
	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance
1	−0.187	−0.144	−0.170	−0.097	−0.231	−0.210	−0.176	−0.127	−0.361	−0.332	−0.167	−0.122
	(−4.06)	(−3.02)	(−1.32)	(−0.70)	(−2.30)	(−2.00)	(−3.38)	(−2.37)	(−2.63)	(−2.34)	(−3.41)	(−2.42)
2	−0.193	−0.113	−0.210	−0.146	−0.180	−0.117	−0.195	−0.112	−0.198	−0.085	−0.193	−0.116
	(−14.08)	(−6.73)	(−5.76)	(−3.23)	(−5.96)	(−3.00)	(−12.86)	(−6.08)	(−4.64)	(−1.59)	(−13.29)	(−6.57)
3	−0.146	−0.080	−0.172	−0.110	−0.107	−0.063	−0.152	−0.083	−0.121	−0.056	−0.149	−0.083
	(−20.68)	(−7.36)	(−8.83)	(−3.69)	(−7.06)	(−2.36)	(−19.52)	(−6.97)	(−5.00)	(−1.67)	(−20.2)	(−7.20)
4	−0.113	−0.081	−0.104	−0.062	−0.110	−0.089	−0.113	−0.079	−0.105	−0.040	−0.114	−0.085
	(−22.67)	(−9.59)	(−8.07)	(−2.77)	(−9.11)	(−4.05)	(−20.86)	(−8.74)	(−6.16)	(−1.55)	(−21.88)	(−9.59)
5	−0.089	−0.067	−0.088	−0.072	−0.087	−0.083	−0.089	−0.065	−0.073	−0.047	−0.090	−0.070
	(−22.54)	(−9.70)	(−8.68)	(−3.92)	(−8.28)	(−4.62)	(−20.97)	(−8.66)	(−5.62)	(−2.08)	(−21.93)	(−9.55)
6	−0.063	−0.047	−0.050	−0.035	−0.079	−0.061	−0.061	−0.045	−0.059	−0.044	−0.064	−0.047
	(−19.47)	(−7.92)	(−5.52)	(−2.15)	(−9.72)	(−4.08)	(−17.28)	(−6.98)	(−6.13)	(−2.38)	(−18.48)	(−7.56)
7	−0.035	−0.035	−0.029	−0.044	−0.052	−0.047	−0.032	−0.033	−0.045	−0.046	−0.034	−0.033
	(−12.2)	(−6.79)	(−4.27)	(−3.15)	(−7.47)	(−3.61)	(−10.4)	(−5.94)	(−6.15)	(−3.33)	(−10.99)	(−6.12)
8	−0.004	−0.007	−0.016	−0.015	−0.017	−0.029	−0.002	−0.003	−0.010	−0.003	−0.003	−0.007
	(−1.29)	(−1.33)	(−2.10)	(−1.09)	(−2.21)	(−2.24)	(−0.54)	(−0.62)	(−1.18)	(−0.18)	(−0.99)	(−1.34)
9	0.029	0.019	0.032	0.017	0.033	0.021	0.028	0.019	0.040	0.011	0.027	0.020
	(9.20)	(3.68)	(3.71)	(1.17)	(4.23)	(1.59)	(8.27)	(3.34)	(4.14)	(0.72)	(8.33)	(3.63)
10a	0.066	0.056	0.056	0.063	0.086	0.092	0.063	0.050	0.061	0.051	0.066	0.056
	(13.99)	(7.50)	(4.25)	(3.20)	(6.67)	(4.70)	(12.44)	(6.28)	(4.03)	(2.38)	(13.40)	(7.11)
10b	0.182	0.155	0.193	0.170	0.229	0.197	0.176	0.149	0.185	0.174	0.182	0.153
	(37.27)	(20.57)	(14.79)	(8.45)	(18.26)	(9.44)	(33.25)	(18.44)	(11.24)	(7.19)	(35.54)	(19.28)
10b − 1	0.369	0.299	0.364	0.266	**0.461**	**0.407**	0.352	0.276	**0.546**	**0.506**	0.349	0.275
	(7.96)	(6.19)	(2.80)	(1.90)	(4.55)	(3.80)	(6.72)	(5.09)	(3.95)	(3.52)	(7.09)	(5.37)

with high and low trading volumes, following Dow record events and front-page market news events.

Table 6 shows the empirical results. All the stocks are ranked into 10 portfolios on the basis of their abnormal trading volumes, with Portfolio 1 as the lowest 10% and Portfolio 10b as the highest 5%. Consistent with Table 1 of Barber and Odean (2008), the first two columns show that on average, the stocks that attract a high degree of attention (Portfolio 10b) have positive net buying flows from households, whereas stocks that attract a low degree of attention (Portfolio 1) have negative net buying flows.

Table 6 also shows the results for the unifying hypothesis. We find that the differences in order flows between the stocks with high and low levels of stock-specific attention are wider following Dow record events and front-page market news events than those on all days. The asymmetric impact of stock-specific attention on buying and selling is more severe after market-wide events that attract a high degree of market attention. Because Dow records are accompanied by higher market returns, we use alternative benchmarks (shown in the third and fourth columns) as the order-flow differences in the periods following days with market returns close to the average market returns on Dow record days. The alternative benchmarks exhibit empirical patterns similar to the original patterns, and the differences in order flows of these benchmarks are lower than those following Dow records. Overall, we find evidence consistent with the unifying hypothesis: Market attention causes investors to be more active, strengthening the cross-sectional impact of stock-specific attention.

The above results provide additional insight into the impact of market-wide attention. After market-wide attention activates investors, stocks with low stock-specific attention should be more likely to exhibit an aggressive net-selling order flow. Although market-wide attention should exert a similar influence across stocks by causing these investors to sell stocks that they hold, stocks with high stock-specific attention are more likely to attract additional purchasing order flow from potential buyers through the mechanism suggested by Barber and Odean, which should counterbalance the selling flow directly produced by market-wide attention. Overall, our study and that of Barber and Odean (2008) complement each other. Those authors essentially argue that stock-specific attention primarily influences "new" investors who have not yet owned the stock. New investors are more likely to purchase attention-grabbing stocks. Existing investors, who have owned the stock, are less likely to be influenced by stock-specific attention, since they already pay attention to the few stocks they hold. We propose that market attention influences existing shareholders' selling decisions, through the disposition effect or rebalancing needs. At the same time, the above empirical results show that market-wide attention strengthens the influence of stock-specific attention on new investors.

7. Conclusion

This paper analyzes the effect of market attention on the stock market. The evidence demonstrates that the impact is pervasive across the market. High market attention causes individual investors in aggregate to reduce their stock positions dramatically — either selling stocks or redeeming mutual fund shares — when the market index is high, and modestly increase their stock positions when the market index is low. The abnormal selling behavior of individual investors following high market attention lowers the market price levels.

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

Our research also has implications for the literature on microstructure. Attention-constrained investors allocate fewer cognitive resources 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 a significant role to it.

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