All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors

Brad M. Barber

Terrance Odean*

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* Barber is at the Graduate School of Management, University of California, Davis. Odean is at the Haas School of Business, University of California, Berkeley. We appreciate the comments of Jonathan Berk, David Blake, Ken French, Simon Gervais, John Griffin, Andrew Karolyi, Sendhil Mullainathan, Mark Rubinstein, Brett Trueman and seminar participants at Arizona State University, the 2002 Behavioral Decision Research in Management Conference, the University of California, Berkeley, the University of California, Irvine, the Copenhagen Business School, Cornell University, Emory, HEC, Ohio State University, the Q Group, the Stockholm School of Economics, the University of Tilburg, Vanderbilt, the Wharton School, the 2001 CEPR/JFI symposium at INSEAD, Mellon Capital Management, the National Bureau of Economic Research, and the Risk Perceptions and Capital Markets Conference, Northwestern University. We are grateful to the Plexus Group, to BARRA, and to the retail broker and discount brokers who provided us with the data for this study and to the Institute for Quantitative Research and the National Science Foundation (grant #SES-0111470) for financial support. Shane Shepherd, Michael Foster, and Michael Bowers provided valuable research assistance. All errors are our own. Brad Barber can be reached at (530) 752-0512 or bmbarber@ucdavis.edu; Terrance Odean can be reached at (510) 642-6767 or odean@haas.berkeley.edu.

Abstract

We test and confirm the hypothesis that individual investors are net buyers of attention-grabbing stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one day returns. Attention-based buying results from the difficulty that investors have searching the thousands of stocks they can potentially buy. Individual investors don't face the same search problem when selling, because they tend to sell only a small subset of all stocks—those they already own. Stocks bought by individual investors on high-attention days tend to subsequently underperform stocks sold by those investors.

How do investors choose the stocks they buy? Are their choices so randomly idiosyncratic that, in aggregate, they cancel out each other and thus have no influence on stock prices? Or do the purchase patterns of investors—even those with heterogeneous beliefs—aggregate in a way that may move price? Several studies document that investors are systematically reluctant to sell stocks for a loss (e.g., Statman and Shefrin, 1985, Odean, 1998a). Less is known about how they make purchases. In this paper, we test the proposition that individual investors simply buy those stocks that catch their attention. While each investor does not buy every single stock that grabs his attention, individual investors are more likely to buy attention-grabbing stocks than to sell them. Systematic buying behavior, like systematic selling, has the potential to influence prices.

In contrast to our findings, many theoretical models of investor trading treat buying and selling as two sides of the same coin. Informed investors observe the same signal whether they are deciding to buy or to sell. They are equally likely to sell securities with negative signals as they are to buy those with positive signals. Uninformed noise traders are equally likely to make random purchases or random sales. In formal models, the decisions to buy and to sell often differ only by a minus sign.[2] For actual investors, the decisions to buy and to sell are fundamentally different.

When buying a stock, investors are faced with a formidable search problem. There are over 7,000 U. S. common stocks from which to choose. Human beings have bounded rationality. There are cognitive—and temporal—limits to how much information we can process. We are generally not able to rank hundreds, much less thousands, of alternatives. Doing so is even more difficult when the alternatives differ on multiple dimensions. One way to make the search for stocks to purchase more manageable is to limit the choice set. It is far easier, for example, to choose among 10 alternatives than 100.

Odean (1999) proposes that investors manage the problem of choosing among thousands of possible stock purchases by limiting their search to stocks that have recently caught their attention. Investors do not buy all stocks that catch their attention; however, for

[2] For example, see the well-cited models of Grossman and Stiglitz (1980) and Kyle (1985).

the most part, they only buy stocks that do so. Which attention-grabbing stocks investors buy will depend upon their personal preferences. Contrarian investors, for example, will tend to buy out–of-favor stocks that catch their eye, while momentum investors will chase recent performers.

In theory, investors face the same search problem when selling as when buying. In practice, two factors mitigate the search problem for individual investors when they want to sell. First, most individual investors hold relatively few common stocks in their portfolio.[3] Second, most individual investors only sell stocks that they already own, that is, they don't sell short.[4] Thus, investors can, one by one, consider the merits—both economic and emotional—of selling each stock they own. Rational investors are likely to sell their past losers, thereby postponing taxes; behaviorally motivated investors are likely to sell past winners, thereby postponing the regret associated with realizing a loss (see Statman and Shefrin, 1985). Thus, to a large extent, individual investors are concerned about the future returns of the stocks they buy but the past returns of the stocks they sell.

Our argument that attention is a major factor determining the stocks individual investors buy, but not those they sell, does not apply with equal force to institutional investors. There are two reasons for this: 1) Unlike individual investors, institutions do often face a significant search problem when selling. Institutions also face many choices when purchasing, but, unlike individuals, they also face many choices when selling. Institutional investors, such as hedge funds, routinely sell short. For these investors, the search set for purchases and sales is identical. Even institutions that do not sell short face far more choices when selling than do most individuals, simply because they own much larger portfolios than do most individuals. 2) Attention is not as scarce a resource for institutional investors as it is for individuals. Institutional investors devote more time to searching for stocks to buy and sell than do most individuals. Institutions use computers to narrow their search. They may limit their search to stocks in a particular sector (e.g., biotech) or meeting specific criteria

[3] On average during our sample period, the mean household in our large discount brokerage dataset held 4.3 stocks worth $47,334; the median household held 2.61 stocks worth $16,210.

[4] 0.29 percent of positions are short positions for the investors in the large discount brokerage dataset that we describe in Section II. When the positions are weighted by their value, 0.78 percent are short.

(e.g., low price-to-earnings ratio) thus reducing attention demands. While individuals, too, can use computers or pre-selection criteria, on average, they are less likely to do so.

In this paper, we test the hypotheses that (1) the buying behavior of individual investors is more heavily influenced by attention than is their selling behavior and that (2) the buying behavior of individual investors is more heavily influenced by attention than is the buying behavior of professional investors. We also develop a model based on the assumption that attention influences buying more than selling and we test the asset pricing predictions of our model. These predictions are (1) that stocks heavily purchased by attention-based investors will subsequently underperform stocks heavily sold by those investors and (2) that this underperformance will be greatest following periods of high attention.

How can we measure the extent to which a stock grabs investors' attention? A direct measure would be to go back in time and, each day, question the hundreds of thousands of investors in our datasets as to which stocks they thought about that day. Since we cannot measure the daily attention paid to stocks directly, we do so indirectly. We focus on three observable measures that are likely to be associated with attention grabbing events: news, unusual trading volume, and extreme returns. While none of these measures is a perfect proxy for attention, all three are useful. An attention grabbing event is likely to be reported in the news. Investors' attention could be attracted through other means, such as chat rooms or word of mouth, but an event that attracts the attention of many investors is usually newsworthy. However, news stories are not all created equal. Major network reporting of the indictment of a Fortune 500 CEO will attract the attention of millions of investors while a routine company press release may be noticed by few. Our historical news data—from the Dow Jones News Service—do not tell us how many investors read each story nor do they rank each story's importance. We infer the reach and impact of events by observing their effects on trading volume and returns.

Trading volume in the firm's stock is likely to be greater than usual when significant news about a firm reaches many investors. Of course, this won't necessarily be the case. Possibly investors will recognize this news to be irrelevant to the firm's future earnings and not trade or investors will all interpret the news similarly and not trade. But significant news will often affect investors' beliefs and portfolio goals heterogeneously, resulting in greater than usual trading. If unusually many investors trade a stock it is nearly tautological that unusually many investors are paying attention to that stock. But high abnormal trading volume could also be driven by the liquidity or information based trades of a few large investors. This is especially true for small capitalization stocks with low average trading volume. While large trades by a few investors may add noise to our calculations, they are unlikely to be driving our results which are as strong, or stronger, for large capitalization stocks as for small.

Important news about a firm often results in significant positive or negative returns. Some news may be difficult to interpret and result in unusually active trading without much price change. But when there is a big price move it is likely that whatever caused the move also caught investors' attention. And even when price is responding to private, not public, information, significant returns will often, in and of themselves, attract attention.

Our three proxies for whether investors were paying attention to a firm are: 1) a stock's abnormal daily trading volume, 2) the stock's (previous) one day return[5], and 3) whether the firm appeared in that day's news. We examine the buying and selling behavior associated with attention for four samples of investors:

- investors with accounts at a large discount brokerage,
- investors at a smaller discount brokerage firm that advertises its trade execution quality,
- investors with accounts at a large retail brokerage, and
- professional money managers.

Our prediction is that individual investors will actively buy stocks on high-attention days. We are not predicting that they will actively trade on high-attention days—that would be nearly tautological when we use abnormal trading volume as a proxy for attention—but, rather, that they will be net buyers.

For every buyer there must be a seller. Therefore, on days when attention-driven investors are buying, some investors, whose purchases are less dependent on attention, must be selling. We anticipate therefore that professional investors as a whole (inclusive of marketmakers) will exhibit a lower tendency to buy, rather than sell, on high attention days and a reverse tendency on low attention days. (Exceptions will arise when the event driving attention coincides with the purchase criteria that a particular professional investor is pursuing.)

As predicted, individual investors tend to be net buyers on high attention days. For example, investors at the large discount brokerage make nearly twice as many purchases as sales of stocks experiencing unusually high trading volume (e.g, the highest five percent)[6] and and nearly twice as many purchases as sales of stocks with an extremely poor return (lowest 5 percent) the previous day. The buying behavior of the professionals is least influenced by attention.

The plan of the paper is as follows. We discuss related research in section I. We describe the four datasets in section II, and our sorting methodology in section III. We develop a model of attention-based buying in section IV, present evidence of attention-based buying in section V, and discuss an alternative hypothesis in section VI. In VII, we test the asset pricing implications of our model and we conclude in section VIII.

I. Related Research

A number of recent studies examine investor trading decisions. Odean (1998a) finds that, as predicted by Shefrin and Statman (1985), individual investors exhibit a disposition effect—investors tend to sell their winning stocks and hold on to their losers. Both individual and professional investors have been found to behave similarly with several types of assets

[5] We use previous day's return, rather than same day return because of potential endogeneity problems. While we argue that extreme price moves will attract buyers, clearly buyers could also cause price moves. Our results are qualitatively similar when we use same day returns as a proxy for attention.

including real estate (Genesove and Mayer), company stock options (Heath, Huddart, and Lang, 1999), and futures (Heisler, 1994; Locke and Mann, 1999) (also see Shapira and Venezia, 1998).

It is well-documented that volume increases on days with information releases or large price moves (Bamber, Barron, and Stober (1997); Karpoff (1987)). For example, when Maria Bartiromo mentions a stock during the Midday Call on CNBC, volume in the stock increases nearly fivefold (on average) in the minutes following the mention (Busse and Green (2002)). Yet, for every buyer there is a seller. In general, these studies to not investigate who is buying and who is selling, which is the focus of our analysis. One exception is Lee (1992). He examines trading activity around earnings announcements for 230 stocks over a one-year period. He finds that individual investors—those who place market orders of less than $10,000—are net buyers subsequent to both positive and negative earnings surprises. Hirshleifer, Myers, Myers, and Teoh (2002) also document that individual investors are net buyers following *both* positive and negative earnings surprises. Lee (1992) conjectures that news may attract investors' attention or, alternatively, that retail brokers—who tend to make more buy than sell recommendations—may routinely contact their clients around the time of earnings announcements.

Odean (1999) examines trading records of investors at a large discount brokerage firm. He finds that, on average, the stocks these investors buy underperform those they sell, even before considering transactions costs. He observes that these investors buy stocks that have experienced greater absolute price changes over the previous two years than the stocks they sell. He points out the disparity between buying and selling decisions for individual investors and the search problem they face when choosing from among thousands of stocks. He suggests that many investors limit their search to stocks that have recently captured their attention, with contrarians buying previous losers and trend chasers buying previous winners.

[6] Looking at all common stock transactions, investors at this brokerage make slightly more purchases (1,082,107) than sales (887,594).

Of course, fully rational investors will recognize the limitations of predominantly buying stocks that catch their attention. They will realize that the information associated with an attention-grabbing event may already be impounded into price (since the event has undoubtedly been noticed by others), that the attention-grabbing event may not be relevant to future performance, and that non-attention-grabbing stocks may present better purchase opportunities. Odean (1998b) argues that many investors trade too much because they are overconfident about the quality of their information. Such investors may overvalue the importance of events that catch their attention, thus leading them to trade sub-optimally. Odean (1999) and Barber and Odean (2000, 2001a, 2001b) find that, on average, individual investors do trade sub-optimally, lowering their expected returns through excessive trading.

Merton (1987) notes that individual investors tend to hold only a few different common stocks in their portfolios. He points out that gathering information on stocks requires resources and suggests that investors conserve these resources by actively following only a few stocks. If investors behave this way, they will buy and sell only those stocks that they actively follow. They will not impulsively buy stocks that they do not follow simply because those stocks happen to catch their attention. Thus their purchases will not be biased toward attention-grabbing stocks.

In recent work, Seasholes and Wu (2004) test our theory in a unique out-of-sample setting. They observe that on the Shanghai Stock Exchange individual investors are net buyers the day after a stock hits an upper price limit. Seasholes and Wu's interpretation of this behavior is that the attention of individual investors is attracted by the event of hitting a price limit and, consistent with our theory, individuals become net buyers of stocks that catch their attention. Also consistent with our theory, Seasholes and Wu document a transitory impact on prices with reversion to pre-event levels within ten trading days. Finally, they identify a small group of professional investors who profit—at the expense of individual investors—by anticipating this temporary surge in price and demand.

II. Data

In this study, we analyze investor trading data drawn from four sources: a large discount brokerage, a small discount brokerage, a large full-service brokerage, and the Plexus Group—a consulting firm that tracks the trading of professional money managers for institutional clients.

The first dataset for this research was provided by a large discount brokerage firm. It includes trading and position records for the investments of 78,000 households from January 1991 through December 1996.[7] The data include all accounts opened by each household at this discount brokerage firm. Sampled households were required to have an open account with the discount brokerage firm during 1991. Roughly half of the accounts in our analysis were opened prior to 1987, while half were opened between 1987 and 1991.

In this research, we focus on investors' common stock purchases and sales. We exclude from the current analysis investments in mutual funds (both open- and closed-end), American depository receipts (ADRs), warrants, and options. Of the 78,000 households sampled from the large discount brokerage, 66,465 had positions in common stocks during at least one month; the remaining accounts held either cash or investments in other than individual common stocks. Roughly 60 percent of the market value in these households' accounts was held in common stocks. There were over 3 million trades in all securities; common stocks accounted for slightly more than 60 percent of all trades. During our sample period, the average household held 4.3 stocks worth $47,334, though each of these figures is positively skewed. The median household held 2.61 stocks worth $16,210. In December 1996, these households held more than $4.5 billion in common stock. There were slightly more purchases (1,082,107) than sales (887,594) during our sample period, though the average value of stocks sold ($13,707) was slightly higher than the value of stocks purchased ($11,205). As a result, the aggregate values of purchases and sales were roughly equal ($12.1 and $12.2 billion, respectively). The average trade was transacted at a price of $31

[7] Position records are through December 1996; trading records are through November 1996. See Barber and Odean (2000) for a more compete description of these data.

per share. The value of trades and the transaction price of trades are positively skewed; the medians for both purchases and sales are substantially less than the mean values.

Our second data set contains information from a smaller discount brokerage firm. This firm emphasizes high quality trade execution in its marketing and is likely to appeal to more sophisticated, more active, investors. The data include daily trading records from January 1996 through June 15, 1999. Accounts classified by the brokerage firm as professionals are excluded from our analysis.[8] The data include 14,667 accounts for individual investors who make 214,273 purchases with a mean value of $55,077 and 198,541 sales with a mean value of $55,999.

The third data set contains information from a large retail brokerage firm on the investments of households for the 30 months ending in June 1999. These data include daily trading records. Using client ownership codes supplied by the brokerage firm, we limit our analysis to the 665,533 investors with non-discretionary accounts (i.e., accounts classified as individual, joint tenants with rights of survival, or custodian for minor) with at least one common stock trade during our sample period. During this period these accounts executed over 10 million trades. We restrict our analysis to their common stock trades: 3,974,998 purchases with a mean value of $15,209 and 3,219,299 sales with a mean value of $21,169.

Our individual investor data include tens of thousands of investors at both discount and retail brokerages. These data are likely to be fairly representative of U.S. individual investors. Our institutional data, however, are more illustrative than representative of institutional investors. The data were compiled by the Plexus Group as part of their advisory services for their institutional clients. The data include daily trading records for 43 institutional money managers and span the period January 1993 through March 1996. Not all managers are in the sample for the entire period. In addition to documenting completed purchases and sales, the data also report the date and time at which the manager decided to make a purchase or sale. In the data, these money managers are classified as "momentum,"

[8] We analyze the accounts of professional investors separately. There are, however, not enough data to achieve statistically significant results.

"value," and "diversified."[9] During our sample period, the eighteen momentum managers make 789,779 purchases with a mean value of $886,346 and 617,915 sales with a mean value of $896,165; the eleven value managers make 409,532 purchases with a mean value of $500,949 and 350,200 sales with a mean value of $564,692; the fourteen diversified managers make 312,457 purchases with a mean value of $450,474 and 202,147 sales with a mean value of $537,947.

III. Sort Methodology

A. Volume Sorts

On the days when a stock experiences abnormally heavy volume, it is likely that investors are paying more attention to it than usual. We wish to test the extent to which the tendency to buy stocks increases on days of unusually high trading volume for each of our four investor groups (large discount, retail, small discount, and professional). First we must sort stocks on the basis of abnormal trading volume. We do so by calculating for each stock on each trading day the ratio of the stock's trading volume that day to its average trading volume over the previous one year (i.e., 252 trading days). Thus, we define abnormal trading volume for stock *i* on day *t*, AV_{it} to be

$$AV_{it} = \frac{V_{it}}{\overline{V}_{it}} \qquad (1)$$

where V_{it} is the dollar volume for stock i traded on day t as reported in the Center for Research in Security Prices (CRSP) daily stock return files for NYSE, ASE, and NASDAQ stocks and

$$\overline{V}_{it} = \sum_{d=t-252}^{t-1} \frac{V_{id}}{252}\,. \qquad (2)$$

Each day we sort stocks into deciles on the basis of that day's abnormal trading volume. We further subdivide the decile of stocks with the greatest abnormal trading volume into two vingtiles (i.e., five percent partitions). Then, for each of our investor types, we sum

[9] Keim and Madhavan (1995, 1997, and 1998) analyze earlier data from the Plexus Group. They classify managers as "technical," "value," and "index." Based on conversations with the Plexus Group, we believe that these classification correspond to our "momentum," "value," and "diversified" classifications.

the buys (B) and sells of stocks (S) in each volume partition on day t and calculate order imbalance for purchases and sales executed that day as:

$$OI_{pt} = \frac{\sum_{i=1}^{n_{pt}} NB_{it} - \sum_{i=1}^{n_{pt}} NS_{it}}{\sum_{i=1}^{n_{pt}} NB_{it} + \sum_{i=1}^{n_{pt}} NS_{it}} \qquad (3)$$

where n_{pt} is the number of stocks in partition p on day t, NB_{it} the number of purchases of stock i on day t, and NS_{it} the number of sales of stock i on day t. We calculate the time series mean of the daily order imbalance (OI_{pt}) for the days that we have trading data for each investor type. Note that throughout the paper our measure of order imbalance considers only executed trades; limit orders are counted if and when they execute. If there are fewer than five trades in a partition on a particular day, that day is excluded from the time series average for that partition. We also calculate order imbalances based on the value rather than number of trades by substituting in the value of the stock i bought (or sold) on day t for NB_{it} (or NS_{it}) in equation 3.3. Note that while total buys and sells increase as volume increases, on a value weighted basis, aggregate buys and sells will increase equally. Thus aggregate value weighted (executed) order imbalance remains zero as abnormal volume increases, and how the order imbalance of a particular investor group changes with volume is an empirical question.

In summary, for each partition and investor group combination, we construct a time-series of daily order imbalance. Our inferences are based on the mean and standard deviation of the time series. We calculate the standard deviation of the time series using a Newey-West correction for serial dependence.

B. Return Sorts

Investors are likely to notice when stocks have extreme one day returns. Such returns, whether positive or negative, will often be associated with news about the firm. The news driving extreme performance will catch the attention of some investors, while the extreme return itself will catch the attention of others. Even in the absence of other information, extreme returns can become news themselves. The Wall Street Journal and other media routinely report the previous day's big gainers and losers (subject to certain price criteria). If big price changes catch investors' attention, then we expect those investors whose buying behavior is most influenced by attention will tend to purchase in response to price changes—both positive and negative. To test the extent to which each of our four investor groups are net purchasers of stocks in response to large price moves, we sort stocks based on one day returns and then calculate average order imbalances for the following day. We calculate imbalances for the day following the extreme returns, rather than the same day as extreme returns, for two reasons. Firstly, many investors may learn of—or react to—the extreme return only after the market closes; their first opportunity to respond will be the next trading day. Secondly, order imbalances could cause contemporaneous price changes. Thus, examining order imbalances subsequent to returns, removes a potential endogeneity problem.[10] Our results are qualitatively similar when we sort on same day returns.

Each day (*t-1*) we sort all stocks for which returns are reported in the CRSP NYSE/AMEX/NASDAQ daily returns file into ten deciles based on the one day return. We further split decile one (lowest returns) and decile ten (highest returns) into two vingtiles. We then calculate the time series mean of the daily order imbalance for each partition on the day following the return sort. This calculation is analogous to that for our sorts based on abnormal volume.[11]

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[10] Endogeneity does not pose the same problem for news and abnormal volume sorts. It is unlikely that the percentage of individual investors' (or institutional investors') trades that is purchases causes contemporaneous news stories. Nor does the percentage of individual investors' (or institutional investors') trades that is purchases cause abnormal trading volume.

[11] Typically a significant number of stocks have a return equal to zero on day t-1. These stocks may span more than one partition. Therefore, before calculating the order imbalance for each partition, we first calculate the average number (and value) of purchases and sales of stocks with returns of zero on day t-1; in subsequent calculations, we substitute this average in place of the actual number (and value) of purchases and sales for zero return stocks. The average number of purchases on day *t* of a stock with a return of zero on day *t-1* is

$$\sum_{s=1}^{S_0} \frac{NB_{st}}{S_0},$$

where S_o is the number of stocks with zero return on day *t-1*. There is an analogous calculation for sales.

where NB_{st} is the number of times stock *s* was purchased by investors in the dataset on day *t* and S_0 is the number of stocks with a return of zero on day *t-1*. Similar calculations are done to determine the average number of sales and the average value of purchases and sales for stocks with a return of zero on day *t-1*.

C. News Sorts

Firms that are in the news are more likely to catch investors' attention than those that are not. Our news dataset is the daily news feed from Dow Jones News Service. The Dow Jones news feed includes the ticker symbols for each firm mentioned in each article We partition stocks into those for which there is a news story that day and those with no news On an average day, our dataset records no news for 91% of the firms in the CRSP database.. The data begin in 1994. Due to how the data were collected and stored some days are missing from the data. . We calculate order imbalances for each firm's stock as described in Section IIIa. Although news is a primary mechanism for catching investors attention, we report our news based results last due to the lack full overlap with our transactions data, missing data, and lack of power.

IV. A Simple Model of Attention-based Buying

The model starts with the assumption that investors buy stocks that catch their attention and illustrates how attention-based buying affects order imbalances for stocks sorted and partitioned with respect to volume and returns. We prove two asset-pricing propositions. The first proposition is generic applying in general to models in which uninformed noise traders trade with informed insiders (e.g., Kyle, 1985). The second proposition is unique to our attention-based buying model. In the model, attention-based noise traders and a risk-neutral, privately informed insider submit market orders to a risk-neutral marketmaker as in Kyle (1985). There are four periods with two rounds of trading. The economy has two assets, a riskless asset and one risky asset. The riskless interest rate is assumed to be 0. The distributions of all market parameters are known to the insider and to the marketmaker. The terminal value of the risky asset is $\tilde{v} = \tilde{y}_1 + \tilde{y}_2$, $\tilde{y}_t \sim N\left(0, \phi^2\right)$ for t = 1, 2. $\tilde{y}_1$ and $\tilde{y}_2$ are independent and can be thought of as the firm's period 1 and 2 earnings. Prior to trading at times t = 1, 2, the risk-neutral insider observes $\tilde{y}_t$. After observing $\tilde{y}_t$, the insider demands (submits a market order for) x_t units of the risky asset; $x_t < 0$ is interpreted to be a sell order. $\tilde{y}_t$ is publicly revealed to the noise traders and to the marketmaker at time t+1, that is, one period after it is observed by the insider. Thus, at t=2, $\tilde{y}_1$ is common knowledge.

The revelation of $\tilde{y}_1$ proxies for news in the model. We assume that, at *t*=2, the level of attention paid to the risky asset by attention-based noise traders is proportional to $\tilde{y}_1^{\,2}$.

Without regard to price or value, noise traders submit market orders to buy $\tilde{b}_t \sim \mathrm{N}\left(\hat{b}_t, \sigma_{bt}^{\,2}\right)$ units and to sell $\tilde{s}_t \sim \mathrm{N}\left(\hat{s}_t, \sigma_{st}^{\,2}\right)$ units of the risky asset. In period two, noise trader buying depends upon the attention generated by news, $\tilde{y}_1$ but, just as in actual markets, not all noise trader activity depends on attention. We set $E\left(\tilde{b}_2 \mid \tilde{y}_1\right) = \hat{b}_2 = m\left(A + \tilde{y}_1^2\right)$, where $m > 0$ is a measure of the intensity of noise trading, $m\tilde{y}_1^2$ is the expected level of attention driven buying, and $mA > 0$ is the expected level of non-attention driven noise trader buying. Setting attention-based buying in period 2 as proportional to $\tilde{y}_1^{\,2}$ captures our assumption that attention based traders will be net buyers on good news (i.e., $\tilde{y}_1 > 0$) or bad news (i.e., $\tilde{y}_1 < 0$) and is consistent with the observation that news tends to focus more intensely on extreme events and consistent with the empirical results reported in section V.b. Our contention is that attention has a greater effect on buying than on selling. So we set $E\left(\tilde{s}_2 \mid \tilde{y}_1\right) = \hat{s}_2 = m\left(A + \kappa\tilde{y}_1^2 + (1-\kappa)\phi^2\right)$, where κ, $0 \le \kappa < 1$, determines how much attention affects selling compared to buying. Note that the unconditional expectations of $\tilde{b}_2$ and $\tilde{s}_2$ are equal, i.e., $E\left(\tilde{b}_2\right) = E\left(\tilde{s}_2\right) = m\left(A + \phi^2\right)$, therefore unconditional net buying (buys minus sells) equals zero. For consistency we also set $\hat{b}_1 = \hat{s}_1 = m\left(A + \phi^2\right)$. Finally, the variances of noise trader buying and selling are assumed to be proportional to the means, that is, $\sigma_{bt}^2 = \hat{b}_{bt} / \psi^2$ and $\sigma_{st}^2 = \hat{s}_{st} / \psi^2$, where $\psi > 0$ is a scaling factor.[12] P_0, the period 0 price of the risky asset, is assumed to equal its unconditional expected terminal value, $\bar{v} = 0$, and P_3, the period 3 price, is set equal to the realized terminal value of the risky asset which is public knowledge in period 3, that is, $P_3 = \tilde{v} = \tilde{y}_1 + \tilde{y}_2$. We are primarily interested in trading at *t* = 2,

[12] In unreported analyses, we confirm that for all three of our attention sort criteria and for investors at all three brokerages the variance of purchases tends to be greater on days that stocks are sorted in high attention partitions. The results are available from the authors.

when the trading activity of noise traders is influenced by the attention associated with the public revelation of the insider's first period signal, $\tilde{y}_1$.

The insider conjectures that the marketmaker's price-setting function is a linear function of total demand $d_t = x_t + \tilde{b}_t - \tilde{s}_t$,

$$P_t = \mu + \lambda d_t \tag{4}$$

He chooses x_t to maximize his expected trading profits, $x_t\left(\tilde{v} - P_t\right)$, conditional on his signal, $\tilde{y}_t$, and the conjectured price function.[13] We assume, as in Kyle (1985), that, due to perfect competition, the marketmaker earns zero expected profits. The marketmaker conjectures that the insider's demand function is a linear function of $\tilde{y}_t$,

$$x_t = \alpha + \beta \tilde{y}_t \,. \tag{5}$$

She sets price to be the expected value of $\tilde{v}$ conditional on total demand, d_t, given the conjectured demand function. Proofs for the equilibrium solution and for the propositions appear in the appendix.

Clearly, from the construction of the model, expected noise trader buying activity is increasing in contemporaneous trading volume and in the square of the previous day's price change. We illustrate this by simulating 100,000 realizations of our model under the assumption that $\phi = 2$, A = 2, m = 2, $\psi = 2$, and $\kappa = 0.5$.[14] As in our empirical analysis, we first sort the simulation realizations into deciles based on period 2 trading volume and period 1 price change and subdivide the largest and smallest return deciles and the largest volume decile into vingtiles. We then calculate period 2 noise trader order imbalance for each partition using the methodology described above in Section II.A.

[13] Because $\tilde{y}_1$ is publicly revealed at t = 2, the risk-neutral insider does not need to consider period two trading when determining his period one demand.

[14] Because $\tilde{b}_t$ and $\tilde{s}_t$ are distributed normally, negative realizations are possible. The likelihood of these depends upon the parameter values. There were no negative realizations of $\tilde{b}_t$ or $\tilde{s}_t$ in this simulation.

In Figure 1a, we see that simulated order imbalance is increasing in volume. The shape of this graph is robust to different choices of parameter values and closely resembles our empirical findings for individual investors which we report in the following section and in Figure 2a. In Figure 1b, we see that the simulated order imbalance is first decreasing and then increasing in the previous period's price change; the plot is convex and U shaped. Again, the shape of the graph is robust to different choices of parameter values and the simulated result resembles our empirical finding for individual investors reported in the following section and in Figure 3a.

Our two propositions examine the model's asset pricing implications:

Proposition 1: Price change from period two to period three is negatively correlated with the period two difference in noise trader buying and selling. Stocks more heavily bought than sold by noise traders tend to underperform. This result is not driven by explicitly by attention but by the willingness of uninformed investors—for any reason—to trade in a market with an informed insider and by the marketmaker's inability to distinguish informed and uninformed trades. A similar effect could be achieved without insider asymmetric information if the marketmaker were risk averse and responded to inventory risk. Note that while the price change from period two to period three is negatively correlated with period two noise trader buying, it is uncorrelated with period one to period two price change, with the period two attention level of noise traders, i.e., $\tilde{y}_1^2$, or with period two total demand, d_2. This is because the rational risk-neutral marketmaker observes $\tilde{y}_1$ and d_2 and sets P_2 equal to $E\left(\tilde{v} \mid \tilde{y}_1, d_2\right)$.

Proposition 2: Expected noise trader losses from period 2 to period 3 are greater when the attention level, $\tilde{y}_1{}^2$, is greater. When the level of attention trading is greater, so too is the volatility of noise trader demand. This makes it more difficult for the marketmaker to detect insider trading. Insider expected profits increase and so do noise trader losses. Together propositions 1 and 2 give us the testable predictions that stocks more heavily bought by attention-based investors will underperform those sold and that this relative underperformance will be greater for stocks that have attracted more attention. We test these predictions in Section VII.

V. Results

A. Volume Sorts

Trading volume is one indicator of the attention a stock is receiving. Table I presents order imbalances for stocks sorted on the current day's abnormal trading volume. Order imbalance is reported for investors at a large discount brokerage, a large retail brokerage, and a small discount brokerage and for institutional money managers following momentum, value, and diversified strategies. Investors at the large discount brokerage display the greatest amount of attention-based buying. When imbalance is calculated by number of trades (column two), order imbalance is negative 18.15 percent for stocks in the lowest volume decile. For stocks in the highest volume vingtile, order imbalance is positive 29.5 percent more. Order imbalance for these investors rises monotonically with trading volume. When imbalance is calculated by value of trades (column three), order imbalance is negative 16.28 percent for stocks in the lowest volume decile. For stocks in the highest volume vingtile, order impalance is positive 17.67 percent. Again, order imbalance increases nearly monotonically with trading volume. Looking at the fourth through seventh columns of Table 1, we see that the net buying behavior of investors at the large retail broker and the small discount brokerage behaves similarly to that of investors at the large discount brokerage.

Our principal objective is to understand how attention affects the purchase decisions of all investors. Calculating order imbalance by the value of trades has the advantage of offering a better gauge of the economic importance of our observations, but the disadvantage of overweighting the decisions of wealthier investors. In trying to understand investors' decision processes, calculating order imbalance by number of trades may be most appropriate. Figure 2a graphs the order imbalance based on number of trades for investors at the large discount brokerage, the large retail brokerage, and the small discount brokerage. Note that the plots are upward sloping as they were in our simulation (Figure 1a).

The last six columns of Table 1 and Figure 2b present the order imbalances of institutional money managers for stocks sorted on the current day's abnormal trading volume. Overall, these institutional investors exhibit the opposite tendency of the individual investors, their order imbalance is greater on low volume days than high volume days. This is particularly true for value managers who are aggressive net buyers on days of low abnormal trading volume.

B. Returns Sorts

Investors are likely to take notice when stocks exhibit extreme price moves. Such returns, whether positive or negative, will often be associated with new information about the firm. Table II and Figures 3a and 3b present order imbalances for stocks sorted on the previous day's return. Order imbalance is reported for investors at a large discount brokerage, a large retail brokerage, a small discount brokerage, and for institutional money managers following momentum, value, and diversified strategies.

Investors at the large discount brokerage display the greatest amount of attention-based buying for these returns sorts. When calculated by number of trades, the order imbalance of investors at the large discount brokerage is 29.4 percent for the vingtile of stocks with the worst return performance on the previous day. Imbalance drops to 1.8 percent in the eighth return decile and rises back to 24 percent for stocks with the best return performance on the previous day. We see in Figure 3a, as was the case in our simulation (Figure 1b), that the order imbalance of these investors is U-shaped when stocks are sorted on the previous day's return.[15] These investors buy attention-grabbing stocks. When imbalance is calculated by value of trades, the order imbalance of these investors is 29.1 percent for the vingtile of stocks with the worst return performance on the previous day. Imbalance drops to negative 8.6 percent in the eighth return decile and rises back to 11.1 percent for stocks with the best return performance on the previous day.

[15] Order imbalances are very similar when we partition stocks on same day's return rather than on the previous day's return.

In Figure 3a, we see that investors at the large retail brokerage also display a U-shaped imbalance curve when stocks are sorted on the previous day's return. However, their tendency to be net buyers of yesterday's big winners is more subdued and does not show up when imbalance is calculated by value. Investors at the small discount brokerage are net buyers of yesterday's big losers but not the big winners.

As seen in the last six columns of Table II and in Figure 3b, the three categories of institutional money managers react quite differently to the previous day's return performance. Momentum managers dump the previous day's losers and buy winners. Value managers buy the previous day's losers and dump winners. Diversified managers do this as well though not to the same extent. While one might interpret purchases of yesterday's winners by momentum managers and the purchases of yesterday's losers by the value managers as attention motivated, it seems more likely that the events leading to extreme positive and negative stock returns coincided with changes relative to the selection criteria that these two groups of money managers follow. Unlike the individual investors, these money managers were not net buyers on high abnormal volume days, nor is any one group of them net buyers following both extreme positive and negative returns.

C. News Sorts

Table III reports average daily order imbalance for stocks sorted into those with and without news. Investors are much more likely to be net buyers of stocks that are in the news than those that are not.[16] When calculated by number for the large discount brokerage, order imbalance is –2.70 percent for stocks out of the news and 9.35 percent for those stocks in the news. At the large retail brokerage, order imbalance is –2.40 percent for stocks out of the news and 16.95 percent for those in the news.

Table III also reports news partition order imbalances separately for days on which individual stocks had a positive, negative, or zero return. Conditional on the sign of the

[16] Choe, Kho, and Stulz (2000) find that individual investors in Korea buy in the days preceding large one day price increases and sell preceding large one day losses. Large one day price moves are likely to be accompanied by news. Choe, Kho, and Stulz point out that the savvy trading of Korean individual investors could result from insider trading.

return, average imbalances for individual investors are always greater on news days than no news days. For both news and no news days, average imbalances are greater for negative return days than for positive return days. One possible explanation for this is that when stock prices drop investors are less likely to sell due to the disposition effect, i.e., the preference for selling winners and holding losers. Alternatively, the differences in imbalances on positive and negative return days may result from the execution of limit orders. Many individual investors will not monitor their limit orders throughout the day. On a day when the market rises, more sell limit orders will execute than buy limit orders. On days when the market falls, more buy limit orders will execute. Unfortunately, our datasets do not distinguish between executed limit and market orders. While both the disposition effect and limit orders may contribute to the greater order imbalance on negative return days, we suspect that limit orders are the primary cause.

To test the robustness of our news sort results, we calculate order imbalances for news and no-news days during four day periods surrounding earnings announcements (the day prior to the announcement, the day of the announcement, and the two days subsequent to the announcement) and during non-earnings announcement periods. For both earnings and non-earnings periods, investors at all three brokerages have a greater propensity to buy (rather than sell) stocks that are in the news.[17]

D. Size Partitions

To test whether our results are driven primarily by small capitalization stocks, we calculate order imbalances separately for small, medium, and large capitalization stocks. We first sort and partition all stocks as described above on the basis of same day abnormal trading volume, the previous day's return, and same day news. We then calculate imbalances separately for small, medium, and large capitalization stocks using the same break points to form abnormal volume and return deciles for all three size groups. We use monthly New

[17] During earnings announcement periods, order imbalance calculated by number of trades at the large discount brokerage is 11.49 percent on days with news and 5.14 percent on days without news; at the small discount brokerage 8.57 percent and -2.67 percent, respectively; and at the large retail brokerage, 7.52 percent and 1.63 percent. During non-earnings announcement periods, order imbalance at the large discount brokerage is 9.01 percent on days with news and 2.53 percent on days without news; at the small discount brokerage, 6.22 percent and –0.75 percent; and at the large retail brokerage 17.32 percent and –2.51 percent.

York Stock Exchange market equity breakpoints to form our size groups.[18] Each month we classify all stocks (both NYSE listed and non-listed stocks) with market capitalization less than or equal to the 30th percentile break point as small stocks, stocks with market capitalization greater than the 30th percentile and less than or equal to the 70th percentile as medium stocks, and stocks with market capitalization greater than the 70th percentile as large stocks. Table IV, reports order imbalances by size group for abnormal volume, return, and news sorts. To conserve space we report imbalances for the investors most likely to display attention-based buying: those at the large discount brokerage. Results for the large retail and small discount brokerages are qualitatively similar.[19]

By and large, investors are more likely to buy rather than sell attention-grabbing stocks regardless of size. This is true for all three of our attention-grabbing measures: abnormal trading volume, returns, and news. Many documented return anomalies, such as momentum and post earning announcement drift, are greater for small capitalization stocks than for large stocks. Some researchers have suggested that these phenomena may be caused by the trading behavior of individual investors. We find, however, that attention-based buying by individuals is as strong for large capitalization stocks as for small stocks. It may be that the individual investor's psychology of investing is similar for large and small stocks but that, due to trading costs and other limits of arbitrage, the impact the individual investor's psychology is greater for small stocks.

VI. An Alternative Hypothesis

An alternative potential explanation for our findings is that different investors interpret attention-grabbing events such as news differently and so such events lead to greater heterogeneity of beliefs. Individual investors who become bullish are able to buy the stock, but those who become bearish can sell it only if they already own it or are willing to sell short. Institutional investors can both buy and sell. On average, bullish individuals and

[18] We thank Ken French for supplying market equity breakpoints. These breakpoints are available and further described at http://web.mit.edu/kfrench/www/Data_Library/det_me_breakpoints.html**.**

[19] The only significant exception to this pattern is that order imbalances at the large retail brokerage for large capitalization stocks are no greater for deciles of high previous day returns than for the middle return deciles. For small cap and medium cap stocks, these retail investors do demonstrate a greater propensity to buy yesterday's winners than yesterday's average performers.

institutions buy while bearish institutions, but not individuals, sell. Thus attention-grabbing events are associated with net buying by individuals, not because individuals are buying what catches their attention, but because attention-grabbing events are increasing heterogeneity of beliefs while limited portfolios and short sale constraints restrict would be sellers. As attention-grabbing events become less recent, they become less salient thereby reducing heterogeneity of beliefs during non-event periods.

While increased heterogeneity of beliefs and selling constraints may contribute to net buying by individuals around attention-grabbing events, we don't think that this is the whole story. We believe that attention plays a major role in determining what stocks investors buy. We further test our attention hypothesis by examining how individual investors buy and sell the stocks that they already own.

Under this alternative hypothesis, attention-grabbing events increase the heterogeneity in investors' beliefs thus leading to trade. Investors without selling constraints are as likely to sell as they are to buy. Investors who already own a stock can sell it. Thus, under this alternative hypothesis, we would expect attention-grabbing events to similarly increase both the sales and the purchases of stocks that investors already own. The attention hypothesis makes a different prediction. The attention hypothesis states that attention is important when investors face a search problem. As discussed above, most individual investors do not face a formidable search problem when choosing a stock to sell, but they do when buying. Stocks they already own compete with thousands of other stocks as potential purchases. Thus attention affects the rate at which stocks are purchased, even stocks that are already owned. Of course investors are, overall, more likely to sell stocks they already own than to buy these stocks. Under the attention hypothesis, however, the order imbalance of stocks that investors already own should be greater on days that those stocks are attention-grabbing.

In Table V, we report order imbalances for individual investors for abnormal volume, return, and news sorts for stocks. In calculating imbalances for this table, we consider only purchases and sales by each investor of stocks he or she already owns. Since investors mostly sell stocks that they already own, but often buy stocks that they do not own, a far greater proportion of these trades are sales. Therefore nearly all of the imbalances are negative. The relative patterns of imbalances are, however, similar to those reported for individual investors in Tables I, II, and III. The ratio of purchases to sales is higher on high attention days. This is particularly true for the abnormal volume sort (Panel A) and the news sort (Panel C). When stocks are sorted on the previous day's return (Panel B), investors are relatively more likely to purchase stocks they already own on days following large negative returns than on other days. However, following large positive returns, order imbalances do not increase as they do for all stocks, regardless of current ownership (as reported in Table II). It is likely that for stocks investors already own, the disposition effect influences their purchases as well as their sales. Odean (1998a) reports that investors are more likely to purchase additional shares of stocks they already own if the share price is below, rather than above, their original purchase price. As predicted by Prospect Theory (Kahneman and Tversky, 1979), investors assume more risk when in the domain of losses than when in the domain of gains. The results in Table V, Panel C are consistent with this.

Thus short-selling constraints (and heterogeneity of beliefs) do not fully explain our findings. For individual investors who can sell a stock without selling short, a higher percentage of their trades are purchases rather than sales on high attention days.

VII. Asset Pricing Predictions

Our theoretical model has two testable predictions. The first is that stocks uninformed investors buy underperform, on average, those they sell. This prediction does not depend on attention and is true in general for models, such as Kyle (1985), in which noise traders and informed traders submit orders and marketmakers use orderflow to set price. Our second, and more critical, prediction is that the underperformance of the stocks bought relative to stocks sold by uninformed attention-based investors will be greatest following periods of high attention.

The model does not specify the period of time over which attention-based buying affects returns. Our evidence that investors do buy stocks that catch their attention is based upon one day sorts. It is likely, though, that investors' attention spans more than a single day.

Furthermore, the period over which the stocks bought by attention-based investors will underperform the stocks they sell depends upon how swiftly the signals of informed investors become public knowledge. In the following analysis, we look for underperformance of stocks bought by attention-based investors over a one month horizon. We obtain similar results at other horizons.

To test the model's first prediction, we form two portfolios: a portfolio of stocks purchased by individual investors and a portfolio of stocks sold by them. We then calculate the difference in the returns of these two portfolios. On each day, we construct a portfolio comprised of those stocks purchased within the last month (21 trading days). The return on the portfolio is calculated based on the value of the initial purchase as:

$$R_t^b = \frac{\sum_{i=1}^{n_{bt}} x_{it} \cdot R_{it}}{\sum_{i=1}^{n_{bt}} x_{it}} \tag{6}$$

where R_{it} is the gross daily return of stock *i* on day *t*, n_{bt} is the number of different stocks purchased during the past month, and x_{it} is the compound daily return of stock *i* from the close of trading on the day of the purchase through day *t-1* multiplied by the value of the purchase. A portfolio of stocks sold within the last month is similarly constructed. For our empirical tests, we compound daily returns to yield a monthly return series. Our prediction is that the returns of the purchase portfolio (R_t^b) will be lower than the returns of the sales portfolio (R_t^s).

To test the second prediction, we first sort stocks into deciles on the basis of the current day's abnormal trading volume and on the basis of previous day's return. For each decile, we form purchase and sale portfolios. Our prediction is that there will be greater underperformance of purchases relative to sales for the high-attention deciles.

We calculate the difference in the returns (R_t^b - R_t^s) for the twenty-one pairs of purchase and sale portfolios (all purchases and sales, ten deciles based on abnormal volume sorts, and ten deciles based on previous day's return sorts). To see whether any observed abnormal returns can be explained by stock characteristics known to affect returns, we employ a four-factor model that includes market, size, value, and momentum factors (Carhart (1997)). For example, to evaluate the return performance of in a particular decile (R_t^b - R_t^s), we estimate the following monthly time-series regression:

$$\left(R_t^b - R_t^s\right) = \alpha_j + \beta_j\left(R_{mt} - R_{ft}\right) + s_j SMB_t + h_j VMG_t + m_j WML_t + \varepsilon_{jt} \ , \qquad (7)$$

where R_{ft} is the monthly return on T-Bills,[20] R_{mt} is the monthly return on a value-weighted market index, SMB_t is the return on a value-weighted portfolio of small stocks minus the return on a value-weighted portfolio of big stocks, VMG_t is the return on a value-weighted portfolio of high book-to-market (value) stocks minus the return on a value-weighted portfolio of low book-to-market (growth) stocks, and WML_t is the return on a value-weighted portfolio of recent winners minus the return on a value-weighted portfolio of recent losers.[21] The regression yields parameter estimates of $\alpha_j, \beta_j, s_j, h_j$ and m_j. The error term in the regression is denoted by ε_{jt}. The subscript *j* denotes parameter estimates and error terms from regression *j*, where we estimate twenty-one regressions.

In Table VI, Panel A, we report the difference in returns earned by purchase and sale portfolios for all trades. We report these separately for each of the three brokerages. Because the short time periods of the large retail and small discount samples, we also report results for the sample of combined trades for investors at all three brokerages.[22] The returns and four-factor alphas for the purchase portfolio minus returns to the sales portfolio are significant and negative only for the large discount brokerage. They are positive, but not significant, for the large discount brokerage and negative, but not significant, for the small discount brokerage and the combined sample. Given the short time periods for the large retail and small discount

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[20] The return on T-bills is from Stocks, Bonds, Bills, and Inflation, 1997 Yearbook, Ibbotson Associates, Chicago, IL.

[21] We construct the *WML* portfolio as in Carhart (1997), though we value-weight rather than equally-weight the momentum portfolio. The construction of the *SMB* and *VMG* portfolios is discussed in detail in Fama and French (1993). We thank Kenneth French for providing us with the remaining data.

[22] The combined return series results in a time-series of monthly returns from February 1991 through June 1999. In months when we have returns from more than one dataset, we average across datasets.

brokerage data, it is not surprising that the results are not statistically significant. We are unable to say whether the observed outperformance of buys minus sells at the retail brokerage is due to chance, to the unusual market conditions in the last few years of the previous century, or to information. The large discount brokerage results offer some support for the first (generic) prediction of our theoretical model.

In Panel B, we report, for the combined sample, returns for the difference in returns earned by purchase and sale portfolios for deciles of stocks first sorted on the current day's abnormal trading volume. In Panel C, we report, for the combined sample, returns for the difference in returns earned by purchase and sale portfolios for deciles of stocks first sorted on the previous day's abnormal return. In all three of our high-attention deciles—decile 10 for the abnormal volume sort and deciles 1 and 10 for the return sort—the underperformance of stocks purchased relative to those sold is both economically and statistically significant. This underperformance is virtually unchanged after accounting for the return factors in the four-factor model. In many of the low attention deciles, the portfolios of stocks purchased outperform portfolios of stocks sold. This outperformance, though generally not reliable, is not explained by our model. But the dramatic drop in purchase portfolio returns minus sale portfolio returns for the high attention deciles is completely consistent with our model and offers it strong support.[23]

VIII. Conclusion

In most economic models, agents make choices that, among the available alternatives, maximize their expected utility. In some models, agents who are faced with a large number of alternatives incur search costs. Though these agents search in an unbiased fashion, costs can prevent them from considering all of their options. In this paper we propose an alternative model of decision making in which agents faced with many alternatives consider primarily those alternatives that have attention attracting qualities. Preferences come into play only after attention has limited the choice set. When alternatives are many and search costs high, attention may affect choice more profoundly than preferences. If the attention grabbing characteristics of an alternative coincide with the characteristics that increase utility, agents may benefit from the role of attention in reducing search costs. However, if attention and utility are orthogonal or negatively correlated, expected utility may be diminished. Under some circumstances, the utility of an alternative is affected by how many agents choose that alternative. Thus the attention attracting qualities of an alternative may indirectly detract from its utility. For example, a well-circulated article about a deserted vacation spot could attract the attention and the travel plans of many vacationers each of whom would be disappointed by the crowds of like-minded tourists.

Attention based decision making has implications for a wide variety of economic situations. In this paper, we test this model of decision making in the context of common stock purchases. Choosing which common stock to buy presents investors with a huge search problem. There are thousands of possibilities. When selling, most investors consider only stocks they already own, which are typically few in number and can be considered one by one. When buying, however, it is impossible—without the aid of a computer—for most investors to evaluate the merits of every available common stock.

We argue that many investors solve this search problem by only considering for purchase those stocks that have recently caught their attention. While they don't buy every stock that catches their attention, they buy far fewer that don't. Within the subset of stocks that do attract their attention, investors are likely to have personal preferences—contrarians, for example, may select stocks that are out of favor with others. But whether a contrarian or a trend follower, an investor is less likely to purchase a stock that is out of the limelight.

Professional investors are less prone to indulge in attention-based purchases. With more time and resources, professionals are able to continuously monitor a wider range of stocks. They are unlikely to consider only attention-grabbing stocks. Professionals are likely to employ explicit purchase criteria—perhaps implemented with computer algorithms—that

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[23] Because we do not have news data for all days, our time series is even shorter when we form portfolios after sorting on news. The difference in returns to the portfolio of buys minus that of sells after sorting on news is not

circumvent attention-based buying. Furthermore, many professionals may solve the problem of searching through too many stocks by concentrating on a particular sector or on stocks that have passed an initial screen.

We test for attention-based buying by sorting stocks on events that are likely to coincide with catching investors' attention. We sort on abnormal trading volume, since heavily traded stocks must be attracting investors' attention. We sort on extreme one-day returns since—whether good or bad—these are likely to coincide with attention-grabbing events. And we sort on whether or not a firm is in the news.

Consistent with our predictions, we find that individual investors display attention-based buying behavior. They are net buyers on high volume days, net buyers following both extremely negative and extremely positive one-day returns, and net buyers when stocks are in the news. Attention-based buying is similar for large capitalization stocks and for small stocks. The institutional investors in our sample—especially the value strategy investors—do not display attention-based buying.

Our theoretical model predicts that when investors are most influenced by attention, the stocks they buy will subsequently underperform those they sell. We find strong empirical support for this prediction. Not only does attention-based buying not benefit investors, but it appears to also influence subsequent stock returns.

The transactional data we analyze are well suited for documenting what investors do, but not as well suited for determining why they do it. We began with a theory which leads to several new testable predictions about how investors behave. Our empirical analysis confirms these predictions and, in so doing, documents previously undocumented patterns in investor behavior. In Section VI, we test one plausible alternative hypothesis to ours. Undoubtedly, readers will look for other alternative explanations for why investors do the things we show they do. To compete with our theory, an alternative theory should predict our results for

significant.

abnormal volume, extreme returns, news, non-binding shortsale constraints, and returns, while offering new predictions of its own.

In previous work, we have shown that most investors do not benefit from active trading. On average, the stocks they buy subsequently underperform those they sell (Odean, 1999) and the most active traders underperform those who trade less (Barber and Odean, 2000). The attention-based buying patterns we document here do not generate superior returns. We believe that most investors will benefit from a strategy of buying and holding a well-diversified portfolio. Investors who insist on hunting for the next brilliant stock would be well advised to remember what California prospectors discovered ages ago: All that glitters is not gold.

Appendix

Lemma 1: An equilibrium exists in which the insider's linear price conjecture, equation 6, and the marketmaker's linear demand conjecture, equation 7, are fulfilled. In equilibrium the coefficients of equations 6 and 7 for period t = 2 are:

$$\alpha = 0 \tag{8}$$

$$\beta = \frac{1}{\psi\phi}\sqrt{m\left(2A+\left(1+\kappa\right)\tilde{y}_1^2+\left(1-\kappa\right)\phi^2\right)} \tag{9}$$

$$\mu = \tilde{y}_1 + \frac{\psi\phi\left(\overline{s}_2-\overline{b}_2\right)}{2\sqrt{m\left(2A+\left(1+\kappa\right)\tilde{y}_1^2+\left(1-\kappa\right)\phi^2\right)}} \tag{10}$$

$$\lambda = \frac{\psi\phi}{2\sqrt{m\left(2A+\left(1+\kappa\right)\tilde{y}_1^2+\left(1-\kappa\right)\phi^2\right)}} \tag{11}$$

Proof: The solutions and proof are for period t = 2. The derivation of equilibrium solutions for period t = 1 is analogous. The insider submits a demand, x_2, that he believes will maximize his expected profit. To do this he solves: $\max_{x_2} E\left(x_2\left(\left(\tilde{v}-P_2\right)\mid \tilde{y}_{1,}\tilde{y}_2\right)\right) = \max_{x_2} E\left(x_2\left(\tilde{v}-\left(\mu+\lambda\left(x_2+\tilde{b}_2-\tilde{s}_2\right)\right)\mid \tilde{y}_{1,}\tilde{y}_2\right)\right)$, (12)

where equation 6 has been substituted for P_2. Taking first-order conditions and solving for x_2, we have

$$x_2 = \frac{E\left(\tilde{v}\mid \tilde{y}_{1,}\tilde{y}_2\right)-\mu+\lambda\left(\hat{s}_2-\hat{b}_2\right)}{2\lambda} = \frac{\tilde{y}_1+\tilde{y}_2-\mu+\lambda\left(\hat{s}_2-\hat{b}_2\right)}{2\lambda}. \tag{13}$$

And so, if the linear conjectures hold,

$$\alpha = \frac{\tilde{y}_1-\mu+\lambda\left(\hat{s}_2-\hat{b}_2\right)}{2\lambda} \text{ and } \beta = \frac{1}{2\lambda}. \tag{14}$$

The marketmaker sets price equal to the expected value of $\tilde{v}$ given the order flow she observes. We can calculate

$$\begin{aligned} P_2 &= E\left(\tilde{v}\mid \tilde{y}_1, d_2\right) \\ &= \tilde{y}_1 - \frac{\beta\phi^2\left(\alpha+\hat{b}_2-\hat{s}_2\right)}{\beta^2\phi^2+\sigma_{b2}^2+\sigma_{s2}^2} + \frac{\beta\phi^2 d_2}{\beta^2\phi^2+\sigma_{b2}^2+\sigma_{s2}^2}. \end{aligned} \tag{15}$$

So, if the conjectures hold,

$$\mu = \tilde{y}_1 - \frac{\beta\phi^2\left(\alpha+\hat{b}_2-\hat{s}_2\right)}{\beta^2\phi^2+\sigma_{b2}^2+\sigma_{s2}^2} \text{ and } \lambda = \frac{\beta\phi^2}{\beta^2\phi^2+\sigma_{b2}^2+\sigma_{s2}^2}. \tag{16}$$

The four equations in 1.9 and 1.11 have four unknowns and are solved by equations 1.3 through 1.6. Thus the conjectures are fulfilled and an equilibrium exists.

Proposition 1: $$\rho_{P_3-P_2,\tilde{b}_2-\tilde{s}_2}=\frac{\operatorname{cov}\left(P_3-P_2,\tilde{b}_2-\tilde{s}_2\right)}{\sqrt{\operatorname{var}\left(P_3-P\right)}\sqrt{\operatorname{var}\left(\tilde{b}_2\right)-\operatorname{var}\left(\tilde{s}_2\right)}}<0 \quad (17)$$

Proof:
Since $\sqrt{\operatorname{var}\left(P_3-P\right)}\sqrt{\operatorname{var}\left(\tilde{b}_2\right)-\operatorname{var}\left(\tilde{s}_2\right)}$ is positive, we need only show that $\operatorname{cov}\left(P_3-P_2,\tilde{b}_2-\tilde{s}_2\right)$ is negative.

$$\begin{aligned}
\operatorname{cov}\left(P_3-P_2,\tilde{b}_2-\tilde{s}_2\right)&=\operatorname{cov}\left(\tilde{y}_1+\tilde{y}_2-\left(\mu+\lambda\left(\tilde{x}_2+\tilde{b}_2-\tilde{s}_2\right)\right),\tilde{b}_2-\tilde{s}_2\right) && \text{from eq. 6}\\
&=\operatorname{cov}\left(\tilde{y}_1+\tilde{y}_2-\left(\mu+\lambda\left(\left(\alpha+\beta\tilde{y}_2\right)+\tilde{b}_2-\tilde{s}_2\right)\right),\tilde{b}_2-\tilde{s}_2\right) && \text{from eq. 5}\\
&=\operatorname{cov}\left(\tilde{y}_1,\tilde{b}_2\right)-\lambda\beta\operatorname{cov}\left(\tilde{y}_1,\tilde{b}_2\right)-\lambda\operatorname{cov}\left(\tilde{b}_2,\tilde{b}_2\right)\text{-}\lambda\operatorname{cov}\left(\tilde{s}_2,\tilde{s}_2\right), && \text{by independence}\\
&=-\lambda\left(\operatorname{var}\left(\tilde{b}_2\right)+\operatorname{var}\left(\tilde{s}_2\right)\right), && \text{since, by symmetry, } \operatorname{cov}\left(\tilde{y}_1,\tilde{b}_2\right)=0. \quad (18)
\end{aligned}$$

Finally, since $\lambda>0$, $-\lambda\left(\operatorname{var}\left(\tilde{b}_2\right)+\operatorname{var}\left(\tilde{s}_2\right)\right)<0$, which is what we wished to show.

Since expected noise trader losses are equivalent to expected insider profits and $\tilde{y}_1^2$ is our measure of the attention level, proposition 2 can be expressed as:

Proposition 2: $$\frac{\delta}{\delta\tilde{y}_1^2}E\left(x_2\left(\tilde{v}-P_2\right)\mid\tilde{y}_1\right)>0 \qquad (19)$$

Proof: Substituting from equations 6 and 7 and for σ_{b2}^2 and σ_{s2}^2, we can write noise trader expected losses as:

$$\begin{aligned}
E\left(x_2\left(\tilde{v}-P_2\right)\mid\tilde{y}_1\right)&=E\left(\left(\alpha+\beta\tilde{y}_2\right)\left(\tilde{y}_2+\tilde{y}_1-\mu-\lambda\left(\alpha+\beta\tilde{y}_2\right)\right)\right)\\
&=\left(\beta-\lambda\beta^2\right)\phi^2 \qquad (20)\\
&=\frac{\phi}{2\psi}\sqrt{m\left(2A+\left(1+\kappa\right)\tilde{y}_1^2+\left(1-\kappa\right)\phi^2\right)}
\end{aligned}$$

The derivative of which, with respect to $\tilde{y}_1^2$, is positive, which is what we wished to show.

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TABLE I: Order imbalance by Investor Type for Stocks Sorted on the Current Day's Abnormal Trading Volume

Stocks are sorted daily into deciles on the basis on the current day's abnormal trading, The decile of highest abnormal trading is split into two vingtiles (10a and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. Order imbalances are reported for the trades of six groups of investors, investors at large discount brokerage (January 1991 through November 1996), investors at a large retail brokerage (January 1997 through June 1999), investors at a small discount brokerage (January 1996 through June 15, 1999), and institutional money managers (January 1993 through March 1996) classified by the Plexus Group as following momentum, value, and diversified strategies. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time-series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage		Momentum Managers		Value Managers		Diversified Managers	
Decile	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 (lowest volume)	-18.15 (0.98)	-16.28 (1.37)	-25.26 (2.11)	-21.26 (1.60)	-20.49 (3.41)	-22.70 (3.88)	14.68 (1.76)	13.74 (2.26)	34.57 (5.54)	33.99 (6.45)	12.52 (2.42)	17.10 (2.91)
2	-8.90 (0.65)	-11.32 (0.98)	-18.78 (1.23)	-20.63 (1.30)	-10.31 (2.30)	-11.02 (2.47)	12.13 (1.07)	11.09 (1.44)	15.20 (2.35)	13.63 (2.91)	14.87 (1.62)	15.06 (1.97)
3	-6.23 (0.52)	-9.49 (0.84)	-15.16 (1.18)	-19.59 (1.18)	-6.95 (1.47)	-7.76 (1.90)	11.38 (0.85)	10.35 (1.15)	10.95 (1.49)	8.43 (1.93)	15.83 (1.28)	11.84 (1.65)
4	-2.76 (0.45)	-8.70 (0.73)	-10.11 (0.99)	-20.07 (1.29)	-4.92 (1.17)	-5.91 (1.56)	12.19 (0.81)	11.89 (1.07)	10.02 (1.23)	4.37 (1.61)	14.92 (1.09)	8.23 (1.50)
5	-0.76 (0.42)	-7.24 (0.67)	-4.82 (1.03)	-17.38 (1.37)	-4.06 (0.77)	-6.80 (1.34)	12.62 (0.72)	12.24 (0.94)	10.90 (1.10)	6.51 (1.38)	13.41 (0.96)	3.97 (1.28)
6	1.65 (0.42)	-7.33 (0.64)	0.23 (1.01)	-16.23 (1.17)	-1.86 (0.81)	-3.33 (1.05)	13.54 (0.70)	13.95 (0.92)	8.73 (1.03)	0.31 (1.32)	12.58 (0.90)	3.31 (1.23)
7	5.45 (0.43)	-2.87 (0.63)	6.69 (1.03)	-13.80 (1.19)	-0.05 (0.74)	-2.58 (0.96)	12.47 (0.65)	13.17 (0.85)	7.25 (0.97)	-0.61 (1.28)	10.99 (0.82)	-0.61 (1.11)
8	9.20 (0.41)	-1.10 (0.62)	13.53 (1.14)	-7.92 (1.16)	1.43 (0.79)	-2.11 (0.86)	11.60 (0.64)	12.11 (0.87)	8.93 (0.95)	1.30 (1.25)	10.80 (0.84)	-0.19 (1.21)
9	13.62 (0.43)	2.86 (0.62)	19.82 (1.27)	-2.02 (1.21)	5.78 (0.62)	1.36 (0.91)	11.33 (0.62)	8.90 (0.93)	7.83 (1.01)	1.09 (1.40)	11.11 (0.89)	3.47 (1.32)
10a	17.72 (0.51)	6.97 (0.75)	22.25 (1.46)	2.62 (1.24)	8.90 (0.83)	3.67 (1.07)	10.84 (0.81)	7.57 (1.22)	7.72 (1.46)	6.38 (2.04)	11.04 (1.20)	5.58 (1.93)
10b (highest volume)	29.50 (0.49)	17.67 (0.73)	19.34 (1.71)	2.02 (1.84)	17.31 (0.98)	11.78 (1.03)	6.72 (0.82)	-0.55 (1.34)	4.83 (1.79)	4.15 (2.44)	8.12 (1.37)	7.23 (2.22)

TABLE II: Order imbalance by Investor Type for Stocks Sorted on the Previous Day's Return

Stocks are sorted daily into deciles on the basis on the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks. The deciles of highest and lowest returns are each split into two vingtiles (1a, 1b, 10a and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. Order imbalances are reported for the trades of six groups of investors, investors at large discount brokerage (January 1991 through November 1996), investors at a large retail brokerage (January 1997 through June 1999), investors at a small discount brokerage (January 1996 through June 15, 1999), and institutional money managers (January 1993 through March 1996) classified by the Plexus Group as following momentum, value, and diversified strategies. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time-series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

Decile	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage		Momentum Managers		Value Managers		Diversified Managers	
	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1a (Negative Return)	29.4 (0.61)	29.1 (0.87)	25.79 (1.60)	22.89 (1.43)	17.32 (1.04)	14.9 (1.43)	-21.03 (1.32)	-30.45 (1.83)	17.26 (3.13)	20.09 (3.41)	10.91 (2.43)	18.08 (2.88)
1b	19.2 (0.54)	16.2 (0.82)	17.86 (1.43)	11.46 (1.57)	11.2 (1.04)	8.58 (1.46)	-6.43 (1.05)	-19.21 (1.56)	14.03 (2.33)	15.62 (2.72)	13.82 (1.75)	15.31 (2.37)
2	13.7 (0.42)	8.8 (0.64)	13.73 (1.17)	5.47 (1.00)	8.65 (0.74)	3.51 (1.20)	-0.62 (0.73)	-14.58 (1.04)	11.19 (1.27)	11.01 (1.73)	14.18 (1.04)	10.47 (2.33)
3	8.9 (0.45)	3.1 (0.63)	6.60 (1.18)	-5.01 (1.09)	3.77 (0.76)	1.23 (1.23)	5.10 (0.71)	-3.72 (0.96)	10.23 (1.06)	7.68 (1.44)	12.30 (0.92)	4.75 (1.29)
4	3.9 (0.45)	-3.3 (0.64)	1.72 (1.06)	-10.98 (1.07)	1.69 (0.84)	-2.75 (1.31)	8.91 (0.76)	4.64 (1.00)	7.98 (0.99)	2.22 (1.34)	11.68 (0.90)	3.04 (1.26)
5	4.1 (0.41)	-3.6 (0.61)	-4.37 (0.95)	-14.36 (0.88)	-0.6 (0.89)	-3.68 (1.40)	9.84 (0.86)	7.02 (1.24)	9.20 (1.29)	3.69 (1.74)	11.56 (1.11)	2.62 (1.63)
6	3.7 (0.42)	-4.2 (0.62)	-3.95 (1.00)	-14.98 (0.95)	-0.99 (0.82)	-3.68 (1.38)	11.07 (0.93)	8.97 (1.28)	9.03 (1.81)	3.52 (2.22)	18.12 (1.34)	9.62 (1.92)
7	2.0 (0.44)	-7 (0.64)	-0.07 (0.91)	-15.23 (1.12)	-1.77 (0.82)	-3.29 (1.28)	15.56 (0.75)	16.36 (0.99)	10.61 (1.18)	1.77 (1.55)	15.39 (0.96)	4.18 (1.36)
8	1.8 (0.42)	-8.6 (0.62)	2.21 (0.84)	-15.85 (0.98)	-1.53 (0.82)	-4.0 (1.27)	19.31 (0.74)	25.22 (0.99)	7.92 (1.06)	0.96 (1.45)	14.00 (0.88)	1.10 (1.30)
9	6.7 (0.43)	-4.8 (0.62)	6.54 (0.88)	-12.80 (1.08)	0.55 (0.73)	-0.79 (1.13)	22.69 (0.69)	32.44 (0.93)	4.30 (1.21)	-6.06 (1.66)	12.99 (1.02)	-1.70 (1.55)
10a	13.4 (0.51)	3.2 (0.78)	6.58 (0.90)	-11.24 (1.17)	1.17 (0.96)	-2.93 (1.41)	24.04 (0.93)	34.75 (1.37)	-4.16 (2.14)	-12.66 (2.57)	10.23 (1.58)	-3.98 (2.24)
10b (Positive Return)	24 (0.52)	11.1 (0.81)	9.01 (0.91)	-7.93 (1.11)	3.8 (0.84)	-3.59 (1.20)	21.50 (1.28)	36.37 (1.74)	-17.32 (3.14)	-16.83 (3.41)	7.57 (2.30)	-0.60 (2.81)

TABLE III: Order Imbalance by Investor Type for Stocks Sorted on the Current Day's News.

Stocks are partitioned daily into those with and without news stories (reported by the Dow Jones News Service) that day. On average there is no news for 91 per cent of stocks. Order imbalances are reported for the trades of six groups of investors, investors at a large discount brokerage (January 1991 through November 1996), investors at a large retail brokerage (January 1997 through June 1999), investors at a small discount brokerage (January 1996 through June 15, 1999), and institutional money managers (January 1993 through March 1996) classified by the Plexus Group as following momentum, value, and diversified strategies. Order imbalances are reported for all stocks and days with or without news. They are also reported separately for the days on which stocks had positive, negative, and zero returns. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time-series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage		Momentum Managers		Value Managers		Diversified Managers	
Partition	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
Panel A: All Days												
News	9.35	0.07	16.17	-2.36	6.76	1.87	13.38	14.00	6.36	-0.24	6.21	2.26
	(0.72)	(0.86)	(1.29)	(1.32)	(0.48)	(0.72)	(1.33)	(1.71)	(1.59)	(2.05)	(1.11)	(1.50)
No News	2.70	-5.62	-1.84	-14.59	-0.66	-4.87	12.20	10.43	10.96	3.62	7.26	1.24
	(0.43)	(0.63)	(0.87)	(0.87)	(0.58)	(1.23)	(1.11)	(1.16)	(1.37)	(1.49)	(0.97)	(0.84)
Panel B: Positive Return Days												
News	1.74	-9.25	14.07	-7.74	1.14	-3.13	22.70	31.95	5.87	-1.01	7.80	3.92
	(0.94)	(1.07)	(1.04)	(1.25)	(0.64)	(0.95)	(1.50)	(2.10)	(1.94)	(2.65)	(1.31)	(2.00)
No News	-2.51	-14.31	1.76	-13.90	-4.49	-8.41	22.39	25.64	14.20	6.67	8.95	6.66
	(0.54)	(0.79)	(0.88)	(1.00)	(0.79)	(1.40)	(1.31)	(1.46)	(1.51)	(1.74)	(1.05)	(1.05)
Panel C: Negative Return Days												
News	17.39	10.91	15.59	3.17	13.77	9.32	3.94	-7.39	4.29	-2.41	4.72	2.24
	(0.83)	(1.12	(1.58)	(1.43)	(0.71)	(1.08)	(1.43)	(2.11)	(2.09)	(2.77)	(1.30)	(2.25)
No News	8.86	3.85	-3.38	-13.57	4.35	1.29	0.68	-8.60	6.92	1.60	5.58	-4.11
	(0.53)	(0.81)	(0.88)	(0.85)	(0.77)	(1.42)	(1.25)	(1.46)	(1.52)	(1.89)	(1.03)	(1.23)
Panel C: Zero Return Days												
News	1.41	-5.90	-0.44	-8.74	1.58	-1.22	14.12	15.16	11.37	9.59	5.21	1.62
	(1.76)	(2.31)	(0.94)	(1.45)	(2.25)	(2.68)	(2.35)	(3.19)	(3.44)	(4.35)	(2.47)	(3.68)
No News	-0.95	-6.40	-14.49	-18.24	-3.27	-7.95	14.60	12.86	10.65	2.42	8.36	-0.17
	(0.68)	(1.13)	(1.06)	(1.08)	(1.35)	(2.04)	(1.38)	(1.81)	(1.73)	(2.49)	(1.27)	(1.84)

TABLE IV: Order Imbalance for Large Discount Brokerage Investors for Stocks Sorted on the Current Day's Abnormal Trading Volume, the Previous Day's return, and the Current Day's News and then Partitioned on Market Capitalization.

In Panel A, stocks are sorted daily into deciles on the basis on the current day's abnormal trading, The decile of highest abnormal trading is split into two vingtiles (10a and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. In Panel B, stocks are sorted daily into deciles on the basis on the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks. The deciles of highest and lowest returns are each split into two vingtiles (1a, 1b, 10a and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. In Panel C, stocks are partitioned daily into those with and without news stories that day (as reported by the Dow Jones News Service). On average there is no news for 91 per cent of stocks. For all three panels, after sorting and partitioning, stocks are further separated into three groups based on market capitalization. We use monthly New York Stock Exchange market equity breakpoints to form our size groups. Each month we classify all stocks (both NYSE listed and non-listed stocks) with market capitalization less than or equal to the 30th percentile break point as small stocks, stocks with market capitalization greater than 30th percentile and less than or equal to the70th percentile as medium stocks, and stocks with market capitalization greater than the 70th percentile as large stocks. Order imbalances are reported for the trades of investors at a large discount brokerage (January 1991 through November 1996). For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time-series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

Panel A: Order imbalance for Stocks Sorted First on Current Day's Abnormal Trading Volume and then on Market Capitalization.

	Small Stocks		Mid Cap Stocks		Large Stocks	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1 (lowest volume)	-16.11 (1.17)	-13.35 (1.50)	-18.43 (2.36)	-17.18 (2.49)	-31.89 (6.32)	-30.33 (6.46)
2	-5.94 (0.86)	-4.37 (1.18)	-12.09 (1.19)	-14.16 (1.50)	-21.44 (2.32)	-22.17 (2.49)
3	-2.23 (0.72)	-2.49 (1.04)	-6.66 (0.85)	-9.24 (1.19)	-15.81 (1.29)	-15.35 (1.56)
4	3.22 (0.71)	0.16 (1.01)	-1.99 (0.70)	-6.65 (1.05)	-9.17 (0.76)	-13.01 (1.11)
5	6.22 (0.70)	2.96 (1.01)	1.54 (0.67)	-4.30 (1.01)	-5.46 (0.58)	-9.99 (0.87)
6	9.44 (0.65)	5.74 (0.96)	2.94 (0.62)	-5.00 (0.95)	-1.24 (0.54)	-9.12 (0.77)
7	10.90 (0.64)	4.47 (0.97)	6.03 (0.59)	-0.99 (0.92)	4.02 (0.54)	-3.27 (0.76)
8	11.83 (0.61)	5.42 (0.92)	6.80 (0.57)	-1.88 (0.89)	9.38 (0.56)	-0.80 (0.77)
9	15.13 (0.53)	7.27 (0.83)	9.27 (0.59)	-0.98 (0.85)	14.50 (0.64)	4.54 (0.84)
10a	16.94 (0.64)	7.73 (0.99)	12.97 (0.76)	3.80 (1.05)	19.76 (0.99)	11.13 (1.22)
10b (highest volume)	20.77 (0.54)	32.13 (0.83)	24.41 (0.86)	15.04 (1.12)	28.26 (1.33)	21.65 (1.53)

Panel B: Order imbalance for Stocks Sorted First on the Previous Day's Return and then on Market Capitalization.

	Small Stocks		Mid Cap Stocks		Large Stocks	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1a (Negative Return)	24.88 (0.66)	26.06 (0.99)	32.71 (1.25)	30.83 (1.48)	38.73 (1.92)	34.55 (2.15)
1b	14.37 (0.65)	12.61 (0.99)	17.61 (0.96)	14.99 (1.27)	25.26 (1.38)	21.93 (1.62)
2	10.69 (0.54)	6.30 (0.82)	9.67 (0.06)	4.99 (0.89)	18.53 (0.67)	13.50 (0.92)
3	6.97 (0.65)	2.05 (0.96)	5.06 (0.59)	-0.95 (0.86)	11.09 (0.59)	5.35 (0.82)
4	4.48 (0.53)	-3.23 (0.78)	0.87 (0.62)	-5.29 (0.90)	4.23 (0.60)	-3.06 (0.81)
5	3.72 (0.42)	-3.64 (0.63)	3.59 (0.46)	-4.45 (0.69)	4.02 (0.47)	-3.58 (0.67)
6	4.20 (0.42)	-3.64 (0.62)	4.46 (0.49)	-3.07 (0.73)	2.86 (0.54)	-4.96 (0.75)
7	5.28 (0.54)	-2.63 (0.79)	2.87 (0.60)	-4.84 (0.90)	0.80 (0.59)	-8.23 (0.81)
8	8.88 (0.61)	2.78 (0.93)	2.07 (0.56)	-7.78 (0.85)	-0.83 (0.58)	-10.96 (0.80)
9	11.98 (0.54)	5.49 (0.83)	6.73 (0.61)	-5.41 (0.90)	3.31 (0.67)	-6.69 (0.90)
10a	16.88 (0.63)	10.59 (0.96)	12.09 (0.82)	2.53 (1.14)	5.53 (1.25)	-1.81 (1.48)
10b (Positive Return)	26.98 (0.57)	18.69 (0.88)	20.85 (1.06)	8.19 (1.33)	7.76 (1.84)	2.94 (2.06)

Panel C: Order Imbalance for Stocks Sorted First on Market Capitalization and then on Current Day's News.

	Small Stocks		Mid Cap Stocks		Large Stocks	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
News All Days	19.87 (1.47)	14.59 (1.85)	13.38 (1.15)	3.87 (1.62)	6.52 (0.85)	-1.35 (0.97)
No News All Days	7.53 (0.48)	2.82 (0.70)	3.12 (0.57)	-4.83 (0.88)	-2.91 (0.67)	-9.86 (0.94)

TABLE V: Order Imbalance for Large Discount Brokerage Investors for Stocks Already Owned by Each Investor. Stocks Sorted on the Current Day's Abnormal Trading Volume, the Previous Day's return, and the Current Day's News.

In Panel A, stocks are sorted daily into deciles on the basis on the current day's abnormal trading, The decile of highest abnormal trading is split into two vingtiles (10a and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. In Panel B, stocks are sorted daily into deciles on the basis on the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks. The deciles of highest and lowest returns are each split into two vingtiles (1a, 1b, 10a and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. In Panel C, stocks are partitioned daily into those with and without news stories that day (as reported by the Dow Jones News Service). Order imbalances are reported for the trades of investors at a large discount brokerage (January 1991 through November 1996), investors at a large retail brokerage (January 1997 through June 1999), and investors at a small discount brokerage (January 1996 through December 1998). Imbalances are calculated for purchases and sales by investors of stocks already held each investor's account. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time-series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

Panel A: Order imbalance for Stocks Already Owned Sorted on Current Day's Abnormal Trading Volume.

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1 (lowest volume)	-54.22 (1.43)	-55.64 (1.89)	-28.74 (1.42)	-33.99 (1.84)	-24.25 (6.28)	-33.22 (7.58)
2	-51.13 (0.78)	-53.20 (1.07)	-29.46 (1.09)	-34.09 (1.36)	-33.80 (3.18)	-29.67 (4.47)
3	-48.27 (0.64)	-49.69 (0.95)	-29.54 (1.04)	-31.25 (1.31)	-31.76 (1.71)	-30.05 (2.44)
4	-47.19 (0.56)	-49.51 (0.88)	-28.69 (0.94)	-32.96 (1.11)	-35.65 (1.26)	-33.93 (1.96)
5	-45.95 (0.53)	-47.59 (0.81)	-26.71 (0.90)	-31.04 (1.07)	-32.34 (1.12)	-30.01 (1.63)
6	-45.01 (0.49)	-48.65 (0.71)	-24.32 (0.90)	-29.71 (1.04)	-30.00 (0.97)	-26.50 (1.42)
7	-42.36 (0.50)	-45.85 (0.71)	-21.83 (0.84)	-30.29 (0.89)	-29.85 (0.95)	-26.21 (1.33)
8	-39.43 (0.51)	-43.75 (0.71)	-18.72 (0.81)	-27.21 (0.87)	-28.20 (0.87)	-26.23 (1.22)
9	-35.64 (0.52)	-40.68 (0.70)	-15.45 (0.78)	-21.79 (0.91)	-27.07 (0.85)	-24.99 (1.21)
10a	-33.03 (0.63)	-39.31 (0.85)	-12.27 (0.97)	-19.97 (1.12)	-26.81 (1.06)	-27.99 (1.42)
10b (highest volume)	-24.97 (0.69)	-32.82 (0.92)	-15.01 (1.04)	-20.04 (1.19)	-17.32 (0.98)	-19.38 (1.42)

Panel B: Order imbalance for Stocks Already Owned Sorted on the Previous Day's Return.

	Large Discount Brokerage		**Large Retail Brokerage**		**Small Discount Brokerage**	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1a (Negative Return)	-9.68	-11.96	4.05	0.33	-16.89	-19.68
	(0.83)	(1.17)	(0.99)	(1.26)	(1.54)	(1.85)
1b	-23.90	-26.00	-8.20	-10.83	-18.90	-21.86
	(0.76)	(1.02)	(0.99)	(1.20)	(1.49)	(1.84)
2	-32.00	-33.15	-12.73	-14.99	-22.71	-24.77
	(0.56)	(0.76)	(0.89)	(1.00)	(1.09)	(1.45)
3	-38.94	-40.22	-18.24	-21.85	-27.10	-26.23
	(0.57)	(0.76)	(0.94)	(0.99)	(1.16)	(1.53)
4	-42.53	-44.79	-20.36	-25.16	-26.03	-26.47
	(0.56)	(0.78)	(0.91)	(1.01)	(1.24)	(1.58)
5	-40.51	-44.29	-20.67	-24.83	-27.67	-27.77
	(0.55)	(0.76)	(0.93)	(1.10)	(1.46)	(1.75)
6	-41.18	-45.31	-21.35	-26.59	-28.54	-27.29
	(0.55)	(0.77)	(0.90)	(1.10)	(1.42)	(1.73)
7	-45.36	-49.57	-22.82	-28.66	-29.28	-28.44
	(0.57)	(0.78)	(0.89)	(1.06)	(1.24)	(1.55)
8	-48.12	-52.42	-25.45	-32.00	-31.14	-28.16
	(0.50)	(0.70)	(0.87)	(1.02)	(1.24)	(1.61)
9	-45.85	-50.13	-27.13	-34.00	-32.70	-28.40
	(0.49)	(0.68)	(0.79)	(0.95)	(1.09)	(1.45)
10a	-40.86	-46.06	-31.17	-38.16	-36.03	-34.85
	(0.64)	(0.89)	(0.85)	(1.03)	(1.27)	(1.67)
10b (Positive Return)	-33.95	-43.77	-29.73	-34.87	-35.02	-38.31
	(0.68)	(0.94)	(0.81)	(1.05)	(1.20)	(1.49)

Panel C: Order Imbalance for Stocks Already Owned Sorted on Current Day's News.

	Large Discount Brokerage		**Large Retail Brokerage**		**Small Discount Brokerage**	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
News All Days	-40.91	-42.36	-15.38	-23.95	-22.14	-22.02
	(0.79)	(0.94)	(0.94)	(0.98)	(0.91)	(1.52)
No News All Days	-45.05	-45.98	-21.42	-25.46	-32.77	-33.68
	(0.52)	(0.77)	(0.92)	(1.02)	(1.00)	(1.52)

Table VI. Percentage return performance for portfolios of stocks purchased minus portfolios of stocks sold in partitions based on abnormal volume sorts, the previous day's return sorts, and new coverage.

Trades data are for investors at a large discount brokerage (LDB—January 1991 through November 1996), investors at a large retail brokerage (LRB—January 1997 through June 1999), and investors at a small discount brokerage (SDB—January 1996 through June 15, 1999). For investors at each brokerage, we form two portfolios: stock purchased and stocks sold. Stocks enter the portfolio the day following the purchase or sale. Portfolios are rebalanced daily assuming a holding period of 21 trading days (i.e., one month). The purchase and sale portfolios are constructed using the value of purchases and sales, respectively. We evaluate the difference in the return of these two portfolios, (R_t^b - R_t^s). We also estimate the following monthly time-series regression:

$$\left(R_t^b - R_t^s\right) = \alpha_j + \beta_j\left(R_{mt} - R_{ft}\right) + s_j SMB_t + h_j VMG_t + m_j WML_t + \varepsilon_{jt} \ ,$$

where R_{ft} is the monthly return on T-Bills, R_{mt} is the monthly return on a value-weighted market index, SMB_t is the return on a value-weighted portfolio of small stocks minus the return on a value-weighted portfolio of big stocks, VMG_t is the return on a value-weighted portfolio of high book-to-market (value) stocks minus the return on a value-weighted portfolio of low book-to-market (growth) stocks, and WML_t is the return on a value-weighted portfolio of recent winners minus the return on a value-weighted portfolio of recent losers. Panel A reports returns and four-factor alphas portfolios based on all trades at each brokerage and for the combined sample. Panels B and C report results for the combined sample sorted on measures of attention. In Panel B, stocks first are sorted daily on the basis on the current day's abnormal trading volume prior to forming purchase and sale portfolios. Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. In Panel C, stocks are first sorted daily into deciles on the basis on the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks.

Panel A. All Purchases and Sales

	Buy Portfolio Return minus Sell Portfolio Return	*t-statistic*	Four-factor Alpha	*t-statistic*
Combined (2/91 to 6/99)	-0.116	-1.450	-0.092	-1.122
LDB (2/91 to 11/96)	-0.244	-2.510	-0.220	-2.080
LRB (2/97 to 6/99)	0.356	1.410	0.214	0.998
SDB (2/96 to 6/99)	-0.035	-0.440	-0.014	-0.150

Panel B. Difference in Percentage Return to Purchase and Sales Portfolios formed after Sorting on the Current Day's Abnormal Trading Volume —Combined (2/91 to 6/99)

Abnormal Volume Sort Decile	Market-adjusted Return	*t-statistic*	Four-factor Alpha	*t-statistic*
1 (Lo)	0.037	0.080	0.029	0.060
2	-0.063	-0.300	-0.036	-0.150
3	0.170	1.010	0.100	0.570
4	0.271	2.040	0.319	2.370
5	-0.020	-0.160	0.026	0.210
6	0.093	0.890	0.064	0.610
7	0.062	0.630	0.075	0.760
8	0.026	0.250	0.043	0.390
9	-0.176	-1.440	-0.195	-1.450
10 (High)	-0.683	-4.130	-0.690	-3.830

Panel C. Difference in Percentage Return to Purchase and Sales Portfolios formed after Sorting on the Previous Day's Return—Combined (2/91 to 6/99)

Return Sort Decile	Market-adjusted Return	*t-statistic*	Four-factor Alpha	*t-statistic*
1 (Negative Return)	-0.338	-1.950	-0.332	-1.770
2	-0.150	-1.420	-0.104	-0.910
3	0.012	0.120	0.010	0.090
4	0.218	1.960	0.250	2.290
5	0.146	0.970	0.178	1.090
6	0.204	1.540	0.267	1.970
7	0.198	2.150	0.209	2.320
8	0.067	0.670	0.079	0.820
9	-0.105	-1.010	-0.116	-1.180
10 (Positive Return)	-0.427	-3.370	-0.510	-3.790

Figure 1: Simulated order imbalance.

We simulate 100,000 realizations of the economy in our model assuming the parameter values assumption that $\phi = 2$, $A = 2$, $m = 2$, $\psi = 2$, and $\kappa = 0.5$. Realizations are sorted into partitions on the basis of period 1 return and period 2 trading volume. Order imbalance is calculated as noise trader buys minus sells divided by noise trader buys plus sells.

Figure 1a

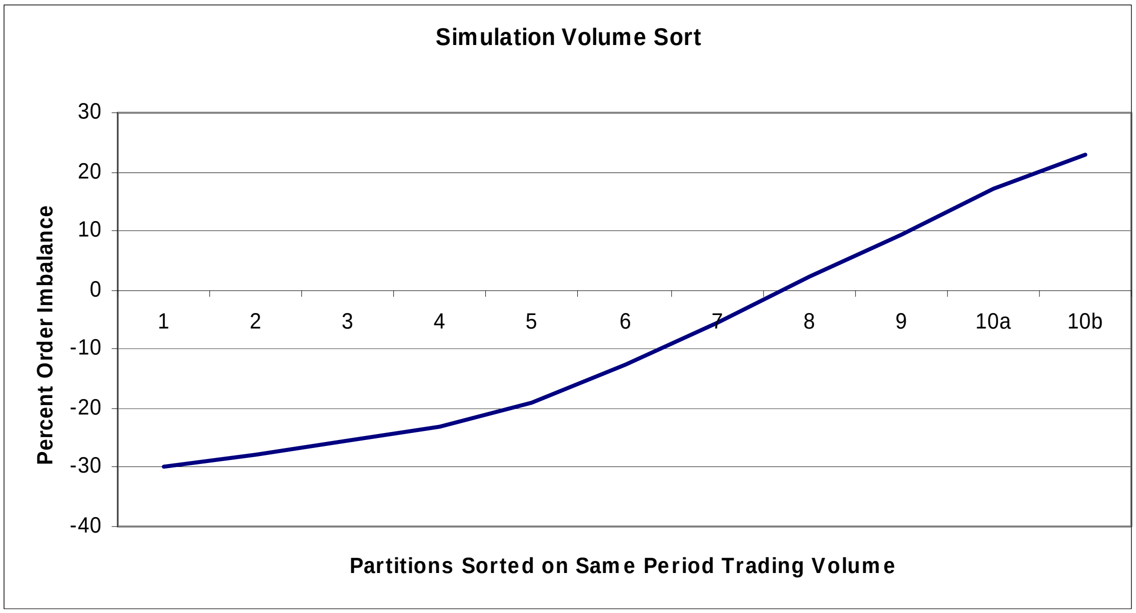

Figure 1b

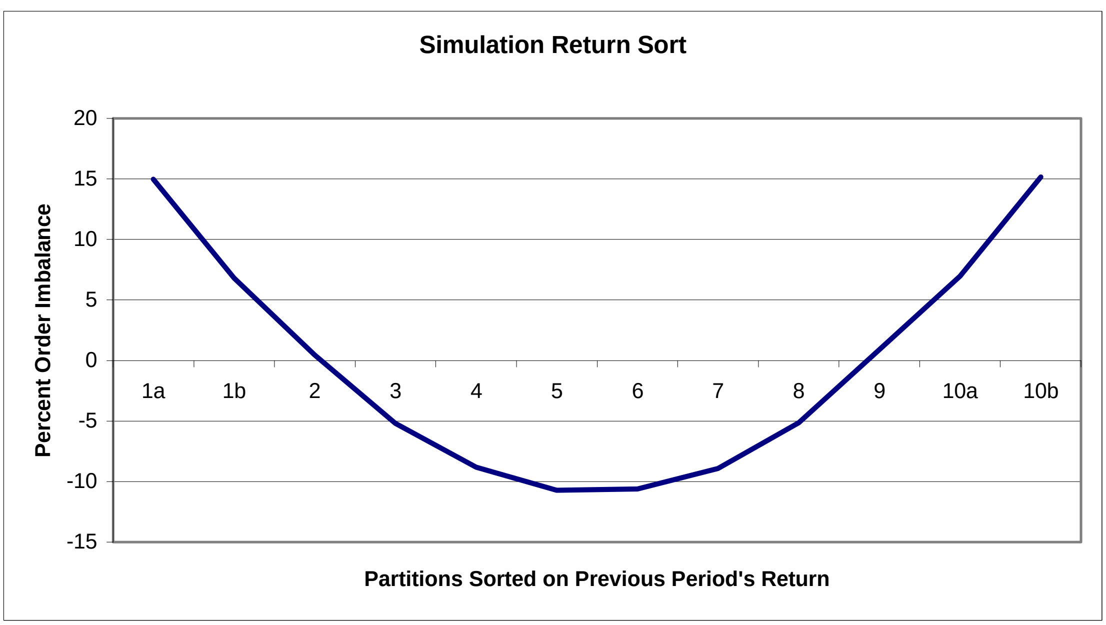

Figure 2: Order imbalance by Number of Trades for Stocks Sorted on the Current Day's Abnormal Trading Volume

Stocks are sorted daily into deciles on the basis on the current day's abnormal trading, The decile of highest abnormal trading is split into two vingtiles (10a and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. Figure 2a graphs order imbalances for investors at a large discount brokerage (1991-1996), investors at a large retail brokerage (January 1997 through June 1999), and investors at a small discount broker (January 1996 through June 15, 1999). Figure 2b graphs order imbalance for institutional money managers (January 1993 through March 1996) classified as following momentum, value, and diversified strategies. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. The figure depicts the mean for each time-series of daily imbalances for a particular investor group.

Figure 2a

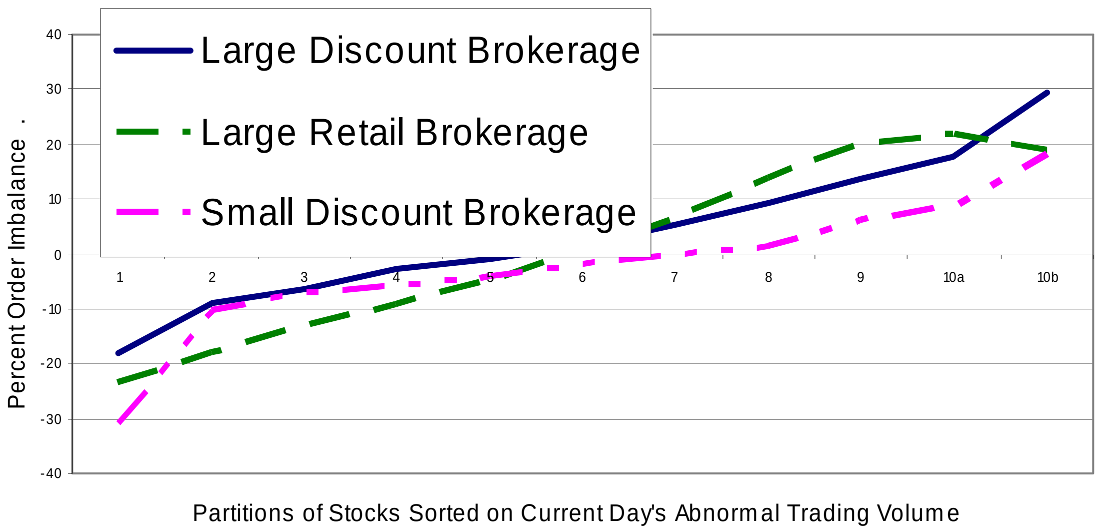

Figure 2b

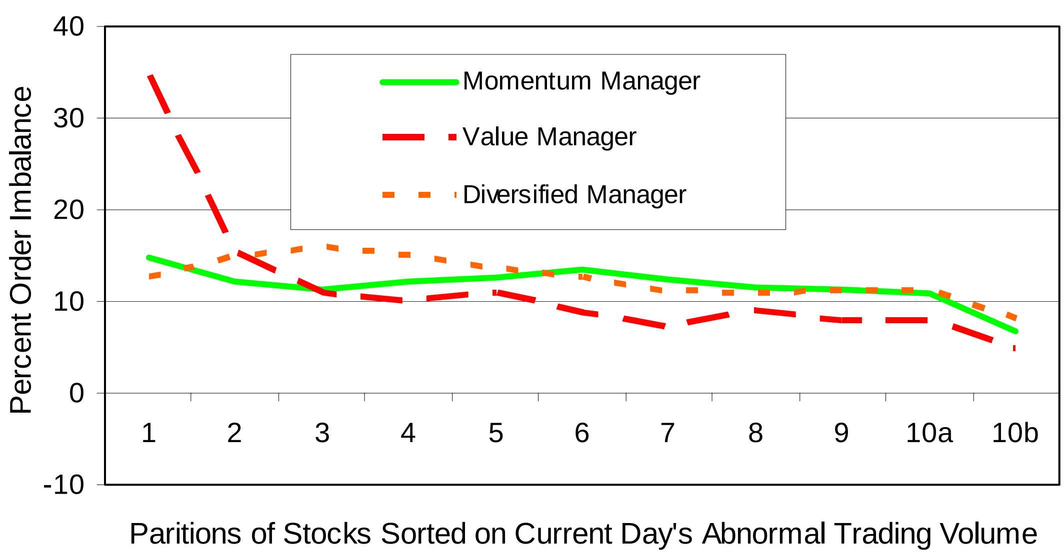

Figure 3: Order imbalance by Number of Trades for Stocks Sorted on the Previous Day's Return

Stocks are sorted daily into deciles on the basis on the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks. The deciles of highest and lowest returns are each split into two vingtiles (1a, 1b, 10a and 10b). Figure 3a graphs order imbalances for investors at a large discount brokerage (1991-1996), investors at a large retail brokerage (January 1997 through June 1999), and investors at a small discount brokerage (January 1997 through June 1999). Figure 3b graphs order imbalances for institutional money managers (January 1993 through March 1996) classified as following momentum, value, and diversified strategies. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. The figure depicts the mean for each time-series of daily imbalances for a particular investor group.