Systematic Noise

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May 2006

* We appreciate the comments of Joseph Chen, Harry DeAngelo, Chris Malloy, Winnie Peng, Allen Poteshman, and Russ Wermers, and seminar participants at the American Finance Association Meetings (San Diego), China International Conference in Finance (Kunming), Cornell University, European Finance Association (Moscow), the New York Society of Quantitative Analysts, the University of California, Berkeley, and the University of Southern California. Shane Shephard provided valuable research assistance. This paper is the merger of earlier separate working papers by Barber and Odean and by Zhu.

Abstract

A substantial literature in institutional herding examines reasons for and evidence of correlated trading across institutional investors, but little has been written about the extent to which individual investor trading is correlated or why. We document that the trading of individuals is highly correlated and surprisingly persistent. Furthermore, we find that the systematic trading of individual investors is driven by their own decisions—trades they initiated—rather than by passive reactions to institutional herding. We discuss why this correlation is unlikely to stem from the same motivations as institutional herding. Correlated trading by individuals is a necessary condition for the trading biases of individual investors to affect asset prices, since the trades of any particular individual are likely to be small. The preferences for buying some stocks while selling others must be shared by many individual investors if these preferences are to affect prices. We analyze trading records for 66,465 households at a large national discount broker between January 1991 and November 1996 and 665,533 investors at a large retail broker between January 1997 and June 1999. Using a variety of empirical approaches, we document that the trading of individuals is more coordinated than one would expect by mere chance. For example, if individual investors are net buyers of a stock this month, they are likely to be net buyers of the stock next month.

In 1986, Fischer Black predicted that, "someday … [t]he influence of noise traders will become apparent." Noise traders are those who "trade on noise as if it were information…. Noise makes financial markets possible, but it also makes them imperfect. If there is no noise trading, there will be very little trading in individual assets" (Black, 1986, p. 529-530). Many theoretical models (e.g., Kyle (1985)) attribute noise traders with random aggregate demand and no persistent or predictable influence on stock prices. Black, though, thought that the influence of noise traders would be cumulative.

While Black did not specify which traders are noise traders, individual investors are prime candidates for the role. According to Black, "[m]ost of the time, the noise traders as a group will lose money trading" (p. 531). Though individual investors earn positive returns in rising markets, they lose money trading (Odean (1999); Barber and Odean (2000), (2001), (2002), Barber, Lee, Liu, and Odean, (2005)); this is particularly true when their trades are ostensibly speculative, that is, not triggered by liquidity demands, tax-losses, or the need to rebalance (Odean, 1999).

For noise trading to affect asset prices, it must be systematic, not self-canceling. Different individual investors must choose the same stocks to buy while selling others; that is, their trading must be correlated. While a substantial literature in institutional herding examines reasons for and evidence of correlated trading across institutional investors[2], little has been written about the extent to which individual investor trading is correlated. We document that the trading of individuals is highly correlated, surprisingly persistent, and not a passive reaction to institutional herding.

Institutional herding could result from principal-agent concerns (Scharfstein and Stein (1990)), informational cascades (Bikhchandani, Hirshleifer, and Welch (1992), and Welch (1992)), or a common rational response to correlated information. In section IV, we argue that these mechanisms are unlikely to coordinate the trading of individual

[2] E.g., Lakonishok, Shleifer, and Vishny (1992), Grinblatt, Titman, and Wermers, (1995), Wermers (1999), and Sias (2002).

investors. We believe, rather, that the trading of individual investors is correlated by shared psychological biases.

Recent studies examine the trading patterns of individual investors and possible psychological motivations for those patterns. For example, individual investors tend to hold on to losing common stock positions and sell their winners (Shefrin and Statman (1985); Odean (1998); Shapiro and Venezia (2001); Grinblatt and Keloharju (2001); Dhar and Zhu, (2002); Jackson (2004)). They also sell stocks with recent gains (Odean (1999); Grinblatt and Kelharju (2001); Jackson (2004)). While most investors buy stocks that have performed well, investors who already own a stock are more likely to buy additional shares if the price is lower than their original purchase price (Odean (1998)). Investors who previously owned a stock are more likely to buy it again if the price has dropped since they last sold it (Barber, Odean, and Strahilewitz (2004)). Investors tend to buy stocks that catch their attention (Barber and Odean (2006)). And investors tend to underdiversify in their stock portfolios (Lewellen, Schlarbaum, and Lease (1974), Barber and Odean (2000), Goetzmann and Kumar (2005)) and in their retirement accounts (Benartzi and Thaler (2001), Benartzi, (2001)).[3]

For the biases and sentiment of individual investors to have a cumulative effect on asset prices, two conditions are necessary. First, there must be limits to the ability and willingness of better informed traders to offset the pricing effects of sentiment driven trading. Second, the aggregate trading of individual investors must be systematic.

The first of these conditions has been addressed both theoretically and empirically. Shleifer and Summers (1990) argue that noise traders may influence prices even in markets where some investors are well informed, because informed traders who wish to profit from their information face risks that are likely to limit their actions.

[3] Other related work includes Kumar (2005) who analyzes the trading patterns of individual investors across style categories, Kumar and Lee (2006) who analyze the relation between individual investor buy imbalance and return anomalies, Goetzmann and Massa (2003) who analyze the impact of S&P 500 index mutual fund flows on market returns, Cohen (1999) who analyzes individual investor purchases and sales of equity and equity mutual funds in response to market returns, and Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2002) who develop a measure of investor sentiment using daily mutual fund flow data.

Suppose, for example, a stock is overvalued (i.e., its price exceeds its fundamental value). If there exists a perfect substitute for the stock and short-selling costs are low, the informed trader can buy the substitute and short-sell the overpriced stock. If enough informed traders do this, the prices of the overpriced security and the substitute will converge. If, however, information is imperfect, no perfect substitute exists, or short-selling costs are high, the informed trader who short sells the overpriced security faces information risk, fundamental risk, and noise trader risk. That is, there is a risk that the informed trader's information is simply incorrect; there is a risk that, although the stock is currently overpriced, subsequent events increase its value and price, in which case the informed trader loses on his trade; and there is a risk that investor sentiment causes the overpriced stock to become even more overpriced (De Long, Shleifer, Summers, and Waldman, 1990), creating losses for the investor whose trading horizon is short or whose cost of carrying a short position is high.

In this paper, we address the second condition necessary for individual investors to affect asset prices. We demonstrate that the trading of individual investors is surprisingly systematic. Furthermore, we find that the systematic trading of individual investors is driven by their own decisions—in the form of market orders—rather than a passive reaction to the trading of institutions.

We examine the trading records of 66,465 investors at a large national discount broker and 665,533 investors at a large national retail broker. Our two main empirical results are quite consistent across the two datasets and can be summarized as follows.

Our first result is that, using several different methods, there is strong evidence of systematic trading by individual investors within a month. For example, in one method, we arbitrarily divide investors from each brokerage into two groups. If trading decisions are independent across investors, they will be uncorrelated across groups. For each group and every stock, we calculate the percentage of trades that are purchases. We then calculate the monthly cross-sectional correlation of the percentage of trades that are buys between groups from the same brokerage. The mean correlation is high: 73 percent for the discount customers and 75 percent for the retail customers. If you know what one group of investors is doing, you know a great deal about what another group is doing.

In contemporaneous research, Jackson (2004) reports that the average correlation of weekly cross-sectional net flows for Australian internet brokers is 29.9 percent and that of Australian full service brokers is 15.9 percent. While Jackson and we document systematic buying and selling in the cross-section of stocks, Kumar and Lee (2006) report that investors at a U.S. discount brokerage are also systematic in their movements of money in and out of equity markets.

Our second main result is that we find strong evidence of systematic trading across months. For example, we sort stocks into deciles based on the percentage of trades that are buys in month *t*. Stocks that are bought by individuals in month *t* are much more likely to be bought by individuals in subsequent months than are stocks sold in month *t*. This persistence extends beyond one year, though it dissipates over time.

In the next section, we describe the data and our empirical methods. We present results in Section II. In Section III, we contrast correlated trading of individual investors with institutional herding and in Section IV we discuss possible reasons why the trading of individual investors is correlated. Section V concludes.

I. Data and Methods

I.A. Trades Data

To analyze the trading behavior of individual investors, we use two proprietary datasets of individual investor trades. In Table 1, we present descriptive statistics for the two databases.

The first data set contains the trades of 66,465 households at a large national discount broker between January 1991 and November 1996. These households made approximately 1.9 million common stock trades – roughly one million buys and 900,000 purchases. The mean value of buys is slightly greater than the mean value of sales. The aggregate values of buys and of sells are roughly equal ($12.1 billion). (See Barber and Odean (2000) for a description of the full dataset.) We also have month-end position statements from January 1991 to December 1996 for these households. The average household held 4.3 stocks (excluding equity mutual funds) worth approximately $47,000.

The second data set contains the trades of 665,533 investors at a large retail broker between January 1997 and June 1999. These investors made approximately 7.2 million trades in common stocks – roughly 4 million buys and 3.2 million sales. As at the discount brokerage, the mean value of buys is greater that the mean value of sales. The aggregate value of buys ($60 billion) is less than the aggregate value of sales ($68 billion). We also have month-end position statements from January 1998 to June 1999 for these households. The average household held 5.5 stocks worth approximately $107,000.

Most of our analyses focus on buying intensity, a term we use throughout the paper to mean the proportion of investor trades that is purchases. In each month, we calculate the proportion of purchases in a particular stock as the number of buys divided by all trades (buys plus sells). (Of course, the proportion of sales is merely one minus the proportion of buys.) We are attempting to measure the tendency of individual investors to buy (or sell) the same set of stocks. Since we will imprecisely estimate this tendency for stocks with few trades during a month, we delete from our analysis stocks with fewer than ten trades during a month.

Employing data from the large discount broker, we measure buying intensity for 3,681 different stocks over our 71-month sample period. In the average month, we measure buying intensity for 572 different stocks. For the average stock, we measure buying intensity in 11 months during our sample period.

Employing data from the large retail broker, we measure buying intensity for 6,862 different stocks over our 30-month sample period. In the average month, we measure buying intensity for 2,543 different stocks. (We are able to measure buying intensity for many more stocks using these data, since we have many more trades in each month.) For the average stock, we measure buying intensity in 11 months during our sample period.

I.B. Distribution Analysis

We employ three approaches to test whether trading decisions are independent across individual investors. We employ the standard measure of herding first used by Lakonishok, Shleifer, and Vishny (1992) in their analysis of institutional trading patterns. Define p_{it} as the proportion of all trades in stock i during month t that are purchases. $E[p_{it}]$ is the proportion of all trades that are purchases in month t. The herding measure essentially tests whether the observed distribution of p_{it} is fat-tailed relative to the expected distribution under the null hypothesis that trading decisions are independent and conditional on the overall observed level of buying ($E[p_{it}]$). Specifically, the herding measure for stock i in month t is calculated as:

$$HM_{it} = \left|p_{it} - E[p_{it}]\right| - E\left|p_{it} - E[p_{it}]\right| \tag{1}$$

The latter term in this measure -- $E\left|p_{it} - E[p_{it}]\right|$ -- accounts for the fact that we expect to observe more variation in the proportion of buys in stocks with few trades (See Lakonishok et al. (1992) for details.)

We also calculate the expected distribution of p_{it} across all stock months under the null hypothesis that trading is independent across investors. This calculation is most easily understood by way of example. Assume we observe 60 percent buys in month t. For stock i, we observe ten trades in month t. We use the binomial distribution with a probability of 0.6 to calculate the probability of observing 0, 10, …, or 100 percent buys out of ten trades. This analysis is done across all stocks and all months to create a simulated distribution of p_{it}.

I.C. Correlation Analysis

I.C.1. Contemporaneous Correlation

Our second approach to test for independent trading decisions is straightforward – we calculate the correlation in the trading decisions of randomly assigned groups. If trading decisions are independent across investors, then the trading decisions of one group will be uncorrelated with the trading decisions of the second group.

Specifically, we partition each of our samples into two arbitrarily determined groups. In each month, we calculate the contemporaneous correlation of buying intensity (i.e., proportion of trades that are buys) across stocks for the two groups at each brokerage.[4] This yields a time-series of contemporaneous correlations. We then average the correlations over time (71 months for the large discount broker and 30 months for the large retail broker). Test statistics are based on the mean and standard deviation of the correlation time series. If the trading decisions of the two groups are random, we would expect the mean correlation in their trading behavior to be zero.

I.C.2. Time Series Correlation

Finally, to test whether buying intensity persists over time, we calculate the correlation of buying intensity across months. For example, we use the proportion buys in each stock to calculate the correlation of buying intensity in consecutive months (i.e., month t and month $t+1$). Since we have 71 months of data for the large discount broker, this yields a time-series of 70 correlations. Since we have 30 months of data for the large retail broker, this yields a time-series of 29 correlations. As before, test statistics are based on the mean and standard deviation of the correlation time series. We calculate mean correlations for lag lengths (L) ranging from one month to two years (24 months).

For each brokerage, we use the two groups described in the prior section. Thus, we formally test four hypotheses for each lag length (L) at each brokerage: Is the correlation of buying intensity in month t and month $t+L$ zero for (1) group one at both

[4] During our sample periods investors are net buyers of common stocks. This does not bias our correlations, because the mean fraction of trades that are purchases is subtracted out when calculating the correlations.

horizons, (2) group two at both horizons, (3) group one in month *t* and group two in month *t+L*, and (4) group two in month *t* and group one in month *t+L*.

As a check on our results, we also partition stocks into deciles based on buying intensity in month *t*. We then calculate the mean buying intensity across stocks for each decile in months *t+L*, where *L=1,…24*.

II. Results

II.A. Distribution Results

In Figure 1, we present the observed and simulated distribution of the percentage of trades that are buys for the discount (panel A) and retail broker (panel B). The bars in the figure represent the observed distribution, while the line represents the simulated distribution. For both datasets, the observed distribution is much flatter than the simulated distribution. The LSV herding measures, which we present in Table 2, are reliably positive for both datasets. We are able to convincingly reject the null hypothesis that trading decisions of individual investors are independent.

II.B. Contemporaneous and Time-Series Correlations

Further evidence on this hypothesis is provided In Table 3. The table presents the mean contemporaneous and time-series correlations of buying intensity. Panel A presents results from the large discount broker, while Panel B contains results for the large retail broker.

The first row of numbers in each panel presents the contemporaneous correlation between the two groups. For both the large discount and large retail broker, there is a strong contemporaneous correlation (greater than 70 percent) in buying intensity. In a given month, both groups tend concentrate their buying in the same stocks.

This correlation has an intuitive interpretation. The square of the correlation is equal to the R-squared from a regression of the buying intensity for group one on the buying intensity of group two. Thus, knowledge about the buying intensity of one group can explain nearly half the variation in buying intensity for the second group.

The remaining rows of each panel present the time-series correlation between buying activity in month *t* and month *t+L*, where *L=1,…24*. For example, the correlation between buying intensity in month *t* and month *t+1* ranges from 46.7 percent to 48.2 percent for the two groups at the large discount broker and from 55.8 to 61.6 percent for the two groups at the large retail broker. The correlations wane over time, but remain reliably positive up through 24 months for both the large discount and large retail broker. Beyond 24 months, the correlations are generally indistinguishable from zero. (We are unable to reliably analyze correlations beyond 24 months for the large retail broker, since we have only 30 months of trade data.) In summary, the results indicate extremely strong persistence in buying intensity over time.

Figures 2a and 2b provide a graphic representation of our results viewed from a slightly different perspective. Each line in each figure represents the mean percentage buys across stocks within deciles formed on the basis of buying intensity in month *0*. Consider first the results for the large discount broker (Figure 2a). For stocks with the greatest buying intensity, on average 90 percent of trades are buys in the formation month; for stocks with the least buying intensity, on average 14 percent of trades are buys in the formation month.

In the months subsequent to decile formation, the spread in buying intensity between the extreme deciles persists. For example, one month after formation, the spread is 36 percentage points (69 percent buys for the top decile and 33 percent buys for the bottom decile). The spread dissipates slowly over time to nine percent after 12 months and four percent after 24 months.

The results for the large retail broker (Figure 2b) are qualitatively similar, though buying intensity is even more persistent for these investors. For example, one month after formation the spread in buying intensity between the extreme deciles is 52 percentage points (69 percent buys for the top decile and 17 percent buys for the bottom decile). The spread dissipates slowly over time to 22 percentage points after 12 months and 15 percentage points after 24 months.

II.C. Results by Firm Size

One reason why individual investors might engage in similar trades is that they experience a common shift in risk aversion. A likely response to changing risk-aversion would be to move money into or out of equity markets. Kumar and Lee (2006) document that investors at the discount brokerage do, indeed, move in and out of the market together. Kumar and Lee attribute correlated movements in and out of the market to changes in investor sentiment, though changing risk aversion or savings patterns could also contribute to this phenomenon. While Kumar and Lee show that individual investors move in and out of the market together, we show that individual investors are systematic in their cross-sectional trading; that is, they are net buyers of some stocks and net sellers of other stocks to a degree far greater than one would expect from chance. Furthermore, we find that this tendency to buy some stocks and sell others is persistent over time.

If shifts in aggregate risk-aversion are driving our results, we would expect to find that investors are systematically buying (selling) low risk stocks while selling (buying) high risk stocks rather than, say, buying some high risk stocks while selling other high risk stocks. Using firm size as a proxy for risk has strong theoretical (Berk (1995)) and empirical foundations (Banz (1981)). We calculate the persistence of buying intensity separately for small, medium, and large stocks. If shifts in risk-aversion are driving our results, we would expect less correlated trading cross-sectionally within size partitions.

We use NYSE breakpoints to determine firm size; the bottom 30 percent are classified as small firms, the middle 40 percent as medium, and the top 30 percent as large. Firms listed on Nasdaq and ASE are placed in size categories based on NYSE cutoffs. We calculate the mean herding measure separately for all stocks, large stocks, medium stocks, and small stocks in each month. Statistical tests are based on the time series of the mean herding measure. The results of this analysis are presented in the last three rows of Table 2. For the discount broker, the herding measure for large stocks is reliably greater than that of all stocks, while the herding measure for small stocks is reliably less than that of all stocks. For the retail broker, the herding measures are very similar across all stocks and within each size class; only the herding measure for large stocks is reliably less than the herding measure for all stocks.

We also analyze the time-series properties of buying intensity within each size class. Figures 3a and 3b provide a graphic representation of our results for the different size categories. Each line in each figure represents the mean percentage buys across stocks for a particular size and order imbalance category. To avoid clutter, we omit the second through ninth order imbalance deciles from the figure. For the large discount broker (Figure 3a), the persistence in order imbalance is qualitatively similar across the different size categories. There is modest evidence that small firms that are heavily sold have less persistence in the selling activity over time. However, this result could also be driven by measurement error, since we have far fewer trades among small firms. With fewer trades, it is likely that our estimate of buying intensity in month *0* is measured less precisely for small firms than large firms (which have many more trades). This is less of an issue for the large retail broker, where we have many more trades in each month. For the large retail broker (Figure 3b), the persistence of buying intensity is virtually identical across the different size categories. The results in Figure 3 are also very similar to those reported for all stocks in Figure 2. These results suggest that the persistence in trading behavior is not driven by movement into and out of different size categories.[5]

III. Institutional Herding

Our study contrasts with the institutional herding literature. Devenow and Welch (1996) point out that while herding could be defined as any behavioral patterns that are correlated across individuals, it more precisely refers to situations where correlated behavior results from individuals observing and reacting to the behavior of others. For example, money managers may choose to “run with the herd” because of principal-agent

[5] Kumar (2005) documents individual investor preferences for small vs. large and value vs. growth stocks change over time. Our results indicate this is not the primary factor coordinating trade across stocks.

concerns, especially when evaluated on relative, rather than absolute, returns (as in Scharfstein and Stein (1990)). Informational cascades can also lead to rational herding when investors recognize that it is more cost effective to rely on the information they infer from the actions of others than to pursue costly private information (see Bikhchandani, Hirshleifer and Welch (1992) and Welch (1992)). Investors may also rationally engage in correlated behavior—but not necessarily react to the behavior of others—when they trade on the same information.

A large number of papers, test for institutional herding. Many report little evidence of herding. Lakonishok, Shleifer, and Vishny (1992) analyze the holdings of pension funds for the five years ending in 1989 and conclude "pension funds herd relatively little." Grinblatt, Titman, and Wermers (1995) analyze the behavior of 155 mutual funds from 1974 to 1985 and conclude that there is "weak evidence that the funds tended to buy and sell the same stock at the same time." Wermers (1999) analyzes all mutual funds over the 1975 to 1999 period and concludes there is "little herding by mutual funds in the average stock." Sias (2002) uses data on all quarterly institutional holdings (from 13-f filings) and finds a "strong positive relation between the fraction of institutions buying over adjacent quarters." If one defines institutional investors to be all investors who are not individuals, then correlated trading by all institutional investors must imply correlated trading by individuals. However, the evidence on the existence of institutional herding and its underlying causes is still not well understood. In contrast to the empirical findings on institutional herding, we document much stronger evidence of coordinated trading by individuals.

The correlated trading behavior of individual investors is, most likely, not driven by the same mechanisms that have been proposed for correlated institutional trading: principal agent concerns, rational information cascades, or a rational response to correlated information.

Principal agent concerns are unlikely to motivate the trading of individual investors, particularly those at a discount brokerage.

Rational informational cascades require that investors are able to observe the behavior of a large group of other investors and that the aggregate signal of the group is valuable. Neither is true for individual investors. First, most individual investors do not have reliable information about the trading of all other individuals. Second, on average, the trades of individual investors are wealth reducing not wealth enhancing (Odean (1999), Barber and Odean (2000, 2001, 2002). Thus, it would not be profitable to mimic the trades of other individual investors. Investors at the retail brokerage could be trading together in response to correlated advice from their brokers. Undoubtedly that is true for some retail customers. However, the level of contemporaneous correlation is very similar for both discount (73.4 percent) and retail investors (75.1 percent).

While investors at the retail brokerage may receive similar advice from their brokers, it is unlikely that the correlated trading by discount investors is a rational response to correlated information, since those investors do not receive formal advice from a common source and, on average, their trades lose money.[6] Furthermore, broker advice cannot explain the long persistence in auto-correlated buying intensity, unless brokers are remarkably unwavering in their specific recommendations.

Finally, as discussed below, the correlated buying and selling behavior of individual investors persists even when one filters out systematically executed limit orders. It is not a passive response to the trading of institutions. Some other mechanisms must be coordinating the active buying and selling decisions of individual investors.

IV. Why are the trades of individuals coordinated?

If the factors that drive institutional herding do not account for the coordinated trading of individual investors, what does? Quite likely several different factors coordinate the trading of individuals investors. Our goal is to establish that coordinated

[6] Feng and Seasholes (2002) document correlated trading over short horizons for investors trading at the same locations in the People's Republic of China. They attribute correlated trading to differences in the prior beliefs of local and distant investors.

trading exists, not to definitively explain its causes. We can, however, suggest factors that may contribute to coordinated trading.

IV.A. Limit vs. Market Orders

One possibility is that the contemporaneous correlation in the buying and selling of individual investors is the result of individual investors reacting passively, via unmonitored limit orders, to the trading demands of institutional investors. To formally test this requires data on market versus limit orders. Unfortunately, the trade data we use do not distinguish limit from market orders. To address the possibility that limit orders are driving our results, we eliminate buys that occur on a day with a negative return and sells that occur on a day with a positive return. The bulk of limit orders are likely to execute on these days. In both datasets, this filter rule eliminates roughly half of all trades. Using the filtered trade data, we recalculate our main results.[7] If unmonitored limit orders are driving our results, we expect to observe less evidence of coordinated trading in the filtered data, which we reasonably expect will contain mostly market orders.

In short, our results are qualitatively similar using the filtered trade data. For example, using the filtered trade data, the contemporaneous correlation of buying intensity between the two groups at the large discount broker is 74 percent – virtually identical to the 73.4 percent reported in Table 3a for the unfiltered data. Similarly, using the filtered trade data, the contemporaneous correlation of buying intensity between the two groups at the large retail broker is 77 percent – also very similar to the 75.1 percent reported in Table 3b for the unfiltered data. The time series auto-correlations of buying intensity for both groups are also qualitatively similar to those reported in Table 3. Our results do not appear to be driven by unmonitored limit orders; the coordinated trading that we documents represents the active decisions of individual investors.

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[7] Since the number of positive and negative return days will vary across stocks, we divide the number of buys by the number of nonnegative return days and sells by the number of nonpositive return days within the month.

Further evidence that our results are not driven by limit orders comes from Barber, Odean, and Zhu (2006) who use the NYSE Trades and Quotes (TAQ) database to show that the buying intensity of investors in our two brokerage datasets is highly correlated with the intensity of buyer initiated small trades (i.e., trades of less than $5,000 or less than $10,000) at the NYSE, ASE, and Nasdaq. The algorithms[8] that they use to sign trades as buyer or seller initiated are specifically designed to identify active, not passive (e.g., limit order), trades.

IV.B. Informed trading

In theory, the trades of individual investors could be coordinated because they share some common valuable information not available to institutions. Evidence suggests otherwise. Several studies find that in aggregate individual investors reduce their returns through trading activity (e.g., Odean (1999), Barber and Odean (2000), Barber, Lee, Liu, and Odean (2005).

IV.C. Psychological biases

Common decision biases may serve to coordinate the trading of individual investors. Three possible biases are limited attention, the disposition effect, and the representativeness bias.

When choosing stock to buy investors face potentially huge search problem with thousands of alternatives. When selling, most investors only consider the few stocks they already own. Barber and Odean (2006) argue that many individual investors cope with the challenge of sifting through thousands of potential purchases, by considering only stocks that otherwise catch their attention. Using news, extreme price moves, and abnormally high trading volume to identify when stocks may catch investors' attention, Barber and Odean find that individual investors are more likely to buy, rather than to sell, attention grabbing stocks.[9] Thus attention appears to be one factor that coordinates individual investor trading.

[8] See Lee and Ready (1991) and Ellis, Michaely, and O'Hara (2000).
[9] Barber and Odean (2006) use the same investor datasets analyzed in this paper as well as additional data.

Individual investors tend to hold onto losing investments and sell winners.[10] This tendency is called the disposition effect (Shefrin and Statman (1985)). The disposition effect will tend to concentrate sales in stocks with strong past returns.

People often make decisions using a representativeness heuristic. They expect small samples and short time series of data to be representative of the underlying population or distribution (Tversky and Kahnemann (1974)). Observing strong recent returns for a security, an investor might conclude that this security is the type (or has become the type) of security that generates strong returns. Thus past performance is extrapolated to the future. DeBondt (1993) uses experimental evidence and surveys to document investors extrapolate past price trends. Barberis, Shleifer, and Vishny (1998) build a regime-switching model of investor sentiment that critically depends on investors using a representativeness heuristic to value stocks. If investors rely on the representativeness heuristic to forecast future stock returns, we would expect them to buy past winners and sell past losers.

To see how, or if, investors react to past returns, we provide a simple graphic representation of the returns on stocks bought and stocks sold using a standard event-time analysis. Specifically, we calculate the mean market-adjusted return on all purchases in event time, where day *0* is the day of the purchase. These means are cumulated beginning three years (756 trading days) prior to the purchase. There is an analogous calculation for sales. In Figure 4, we present the cumulative mean market-adjusted return for buys and sells; panel A contains results for the discount broker, while panel B contains results for the retail broker. It is clear from this graph that investors buy *and* sell stocks with strong past returns. For both the datasets, stocks bought, on average, outperform the market by 70 percentage points over three years prior to purchase. Stocks sold also outperform the market, but not by such a large margin.

[10] See Odean (1998), Barber and Odean (1999),Genesove and Mayer (2001) Heath, Huddart, and Lang (1999), Locke and Mann (2000), Shapira and Venezia (2001), Grinblatt and Keloharju (2001).

It is informative to analyze the returns of stocks bought less the returns of stocks sold. For both brokers, this difference is positive prior to the day of the trade indicating the preferences for buying stocks with strong past returns is greater than the preference for selling stocks with strong past returns. However, this difference peaks well before day 0 for both brokers, indicating the preference for selling stocks with strong recent returns is greater than the preference for buying stocks with strong recent returns.

V. Conclusion

The buying and selling behavior of individual investors is systematic. The contemporaneous correlation in which stocks individual investors are buying or selling is high. For our samples of 66,465 investors at a large national discount broker and 665,533 investors at a large retail broker, this correlation is about 75 percent. What investors buy this month is also correlated with future buying. We document up to 24 months of positive lagged correlations in investors' purchase and sale decisions.

Our goal has been to establish that the buying and selling behavior of individual investors is systematic, not to definitively determine the causes of this systematic behavior. We do, however, consider possible coordinating factors. We argue that it is unlikely that the trades of individual investors are coordinated by the same factors that contribute to institutional herding such as principal agent concerns, rational information cascades, or a rational response to correlated information. The coordinated trading of individual investors also does not stem primarily from individual investor limit orders executing in reaction to active trading by institutional investors or from aggregate shifts in the risk-aversion of individual investors. Shared psychological biases such as limited attention, the disposition effect, and the representativeness heuristic do appear to contribute to coordinated trading. But other factors, such as tax-loss selling, may also help to coordinate these trades.

The influence of one individual investor on asset prices is negligible. However, we find that buying and selling decisions of individuals are highly correlated and they cumulate over time. Thus individual investors, sometimes referred to as noise traders, do have the potential to affect asset prices because their noise is systematic.

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Table 1: Descriptive Statistics on Trades Data

	Discount	Retail
Period	January 1991 to November 1996	January 1997 to June 1999
Number of Households	66,465	665,533
Number of Accounts	104,211	793,499
Number of Buys	1,082,107	3,974,998
Mean (Median) Buy Value	$11,205 ($4,988)	$15,209 ($7,135)
Number of Sells	887,594	3,219,299
Mean (Median) Sell Value	$13,707 ($5,738)	$21,170 ($7,975)

Table 2: Tests for Independence of Trades for All Stocks and by Size Classification

Herding measurement for stock i in month t $HM_{i,t} = |p_{i,t} - E[p_{i,t}]| - E|p_{i,t} - E[p_{i,t}]|$ where $p_{i,t}$ is the proportion of all trades in stock i during month t that are purchases, $E[p_{i,t}]$ is the proportions of all stock traded by sample individual investors during month t that are purchases, and $|p_{i,t} - E[p_{i,t}]|$ is the proportion of all trades in stock i during month t that are purchases minus the proportions of all stock traded by sample individual investors during month t that are purchases. $E|p_{i,t} - E[p_{i,t}]|$ is an adjustment factor, which varies depending on the overall buying activity in all stocks during the month and the number of trades in stock i during month t. We restrict our analysis to stocks with at least 10 trades in month t. In each month, we average herding measures across stocks. Statistical tests are based on the time-series of the mean herding measure across stocks. Herding measures for large, medium, and small firms are calculated by restricting the analysis to stocks that fall into each size category. Size cutoffs are based on NYSE market cap breakpoints, where the top 30 percent are classified as large firms, the bottom 30 percent as small, and the remaining firms as medium. (p-values are in parentheses.)

	Discount Broker	Retail Broker
All Stocks	0.0681	0.1279
	(<0.001)***	(<0.001)***
Large	0.0758	0.1138
	(<0.001)***	(<0.001)***
Medium	0.0659	0.1313
	(<0.001)***	(<0.001)***
Small	0.0537	0.1250
	(<0.001)***	(<0.001)***

Table 3: Mean Contemporaneous and Time-Series Correlation of Percentage Buys by Individual Investors

Results are based on trades data from a large discount broker (1/91 to 11/96) and a large retail broker (1/97 to 6/99). We break each dataset up into two equal groups of investors. For each stock in each month, we calculate the percentage of all trades that are purchases. The table presents the mean contemporaneous correlation across groups in the first row of each panel. The remaining rows represent the mean temporal correlation from one to 24 months. The correlation of group one with group two represents the temporal correlation of percentage buys by group one in month *t* with the percentage buys by group two in month *t+L*, where *L=1,24*. (Results for group two with group one are qualitatively similar and not presented.) t-statistics are based on the mean and standard deviation of the calculated correlations.

Panel A: Large Discount Broker (1/91 to 11/96)						
	Correlation of % Buys in Month *t* with % Buys in Month *t+L*			*t*-statistics		
Horizon (*L*):	Group 1 with Group 1	Group 2 with Group 2	Group 1 with Group 2	Group 1 with Group 1	Group 2 with Group 2	Group 1 with Group 2
0	100.0%	100.0%	73.4%	n.a.	n.a.	124.04*
1	48.2	46.7	47.7	51.63*	55.15*	48.98*
2	34.1	33.1	33.7	29.61*	29.19*	27.91*
3	27.2	26.3	27.3	22.05*	21.34*	22.89*
4	21.7	21.7	21.3	21.32*	20.54*	18.11*
5	17.7	18.4	18.8	15.28*	15.61*	15.87*
6	17.1	16.4	17.9	13.96*	14.67*	15.00*
7	14.9	14.2	15.9	11.69*	12.74*	13.75*
8	14.5	12.5	14.5	12.39*	10.17*	12.58*
9	15.2	11.4	14.4	9.80*	8.12*	9.73*
10	12.6	10.8	12.0	10.29*	8.73*	10.25*
11	9.9	8.8	10.3	10.09*	7.69*	9.62*
12	9.7	8.8	9.6	9.31*	7.72*	8.11*
13	7.9	6.4	7.4	6.69*	4.74*	5.14*
14	7.5	5.9	7.7	5.41*	4.67*	5.42*
15	6.7	4.2	6.1	4.68*	2.83*	4.24*
16	4.8	4.0	6.0	3.12*	3.13*	4.48*
17	6.7	5.9	6.5	5.13*	4.06*	4.98*
18	6.3	6.3	6.2	4.15*	3.78*	4.04*
19	4.8	4.3	5.1	2.69**	2.76*	3.06*
20	6.0	3.7	6.3	3.79*	2.29**	3.71*
21	7.2	3.5	6.2	4.54*	2.20**	3.87*
22	4.3	4.1	6.2	2.99*	2.43**	3.67*
23	5.2	4.2	4.8	3.21*	3.10*	3.87*
24	5.1	3.1	4.6	3.19*	2.22**	3.73*

Panel B: Large Retail Broker (1/97 to 6/99)						
	Correlation of % Buys in Month t with % Buys in Month t+i			*t*-statistics		
Horizon (*i*):	Group 1 with Group 1	Group 2 with Group 2	Group 1 with Group 2	Group 1 with Group 1	Group 2 with Group 2	Group 1 with Group 2
0	100.0%	100.0%	75.1%	n.a.	n.a.	156.31*
1	56.7	58.6	55.8	96.02*	41.14*	71.58*
2	45.8	46.4	45.5	86.48*	31.20*	78.07*
3	39.8	40.8	41.1	57.92*	27.22*	67.20*
4	36.5	34.9	36.5	67.14*	24.50*	55.31*
5	32.4	31.9	34.1	73.84*	22.75*	53.86*
6	30.5	30.1	31.8	45.24*	22.11*	41.81*
7	28.9	27.3	29.9	29.38*	19.39*	31.14*
8	27.8	25.7	28.9	36.04*	17.12*	31.59*
9	25.5	24.8	26.4	24.83*	16.28*	24.45*
10	23.7	21.3	24.7	22.04*	15.64*	21.35*
11	23.2	20.7	23.2	18.87*	18.05*	20.95*
12	22.7	20.8	23.1	20.34*	19.54*	20.35*
13	19.9	18.4	20.8	16.75*	16.18*	17.59*
14	18.6	17.4	18.8	13.81*	23.09*	16.94*
15	17.1	17.1	17.3	10.49*	20.44*	14.38*
16	16.4	17.6	17.1	11.79*	20.89*	11.64*
17	14.9	16.9	16.8	12.28*	17.29*	12.71*
18	14.9	16.9	15.0	12.34*	14.88*	12.84*
19	12.2	16.9	14.4	8.42*	14.48*	8.65*
20	12.8	16.9	13.2	14.96*	12.73*	11.78*
21	12.9	18.0	13.4	12.04*	12.44*	13.36*
22	13.9	18.2	13.0	9.05*	10.05*	8.21*
23	15.9	19.9	15.6	9.17*	10.04*	8.88*
24	16.6	22.6	17.4	14.38*	10.99*	15.30*

*, ** - significant at the one and five percent level, respectively.

Figure 1: Observed and Simulated Distribution of Percentage Buys

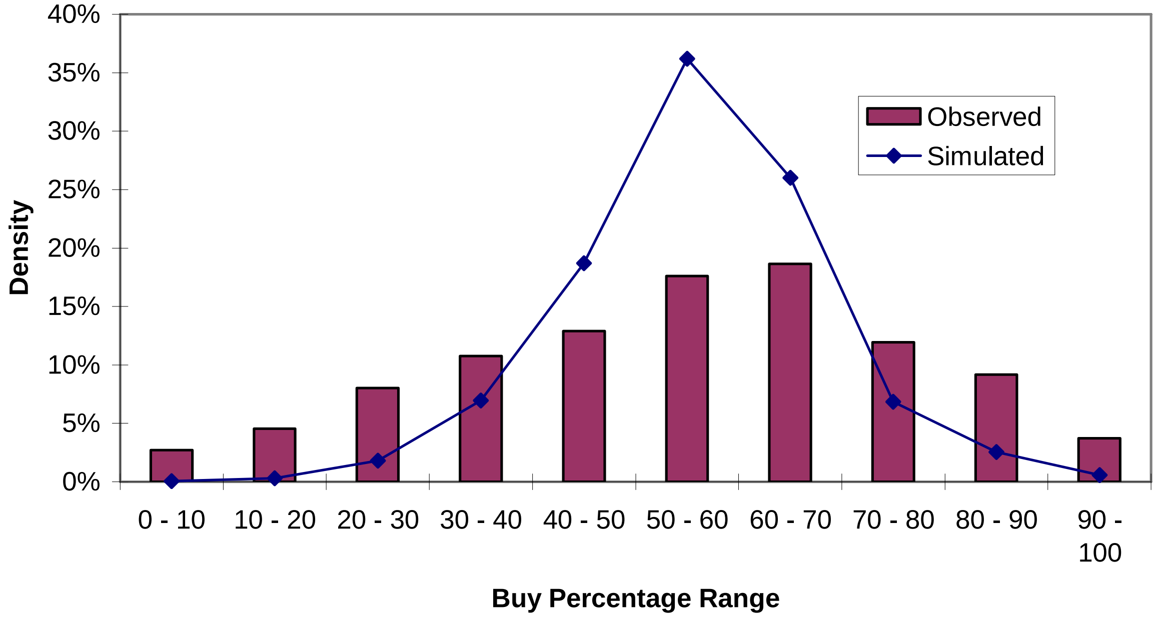

Figure 1a: Large Discount Broker, 1991 to 1996

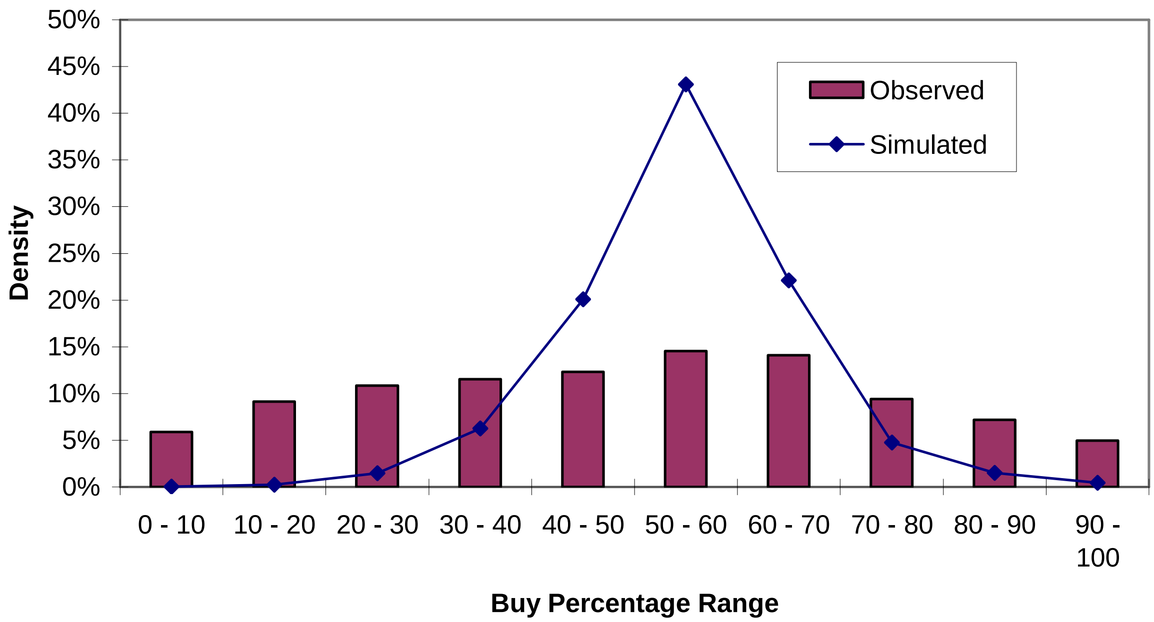

Figure 1b: Large Retail Broker, 1997-1999

Figure 2: Percentage Buys in Event Time

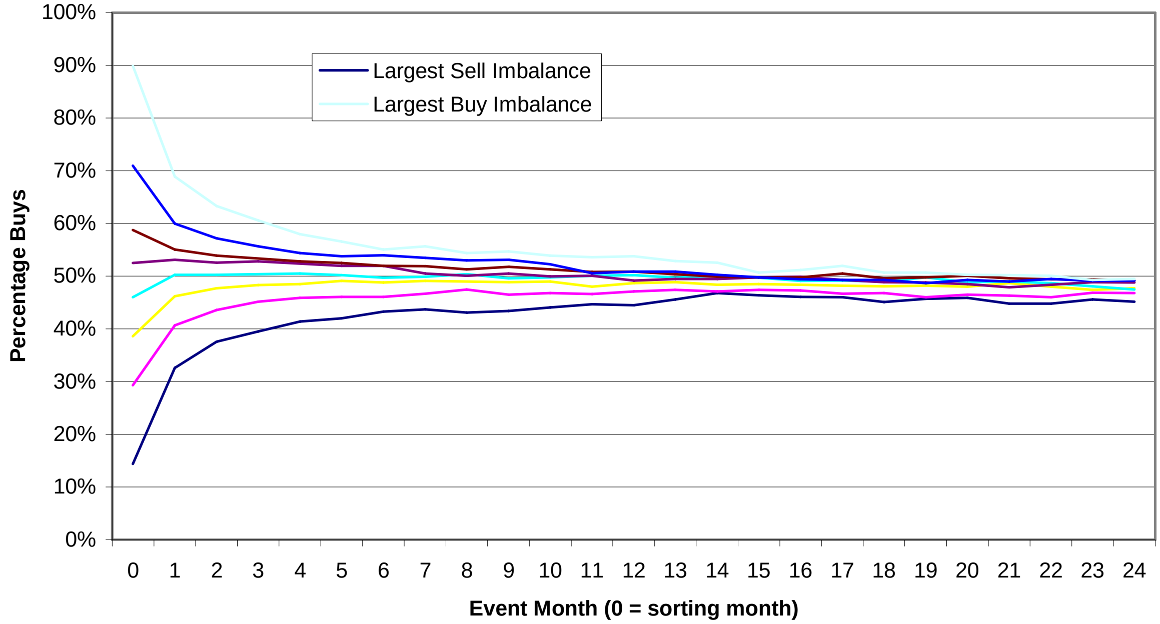

Figure 2a: Large Discount Broker, 1991-1996

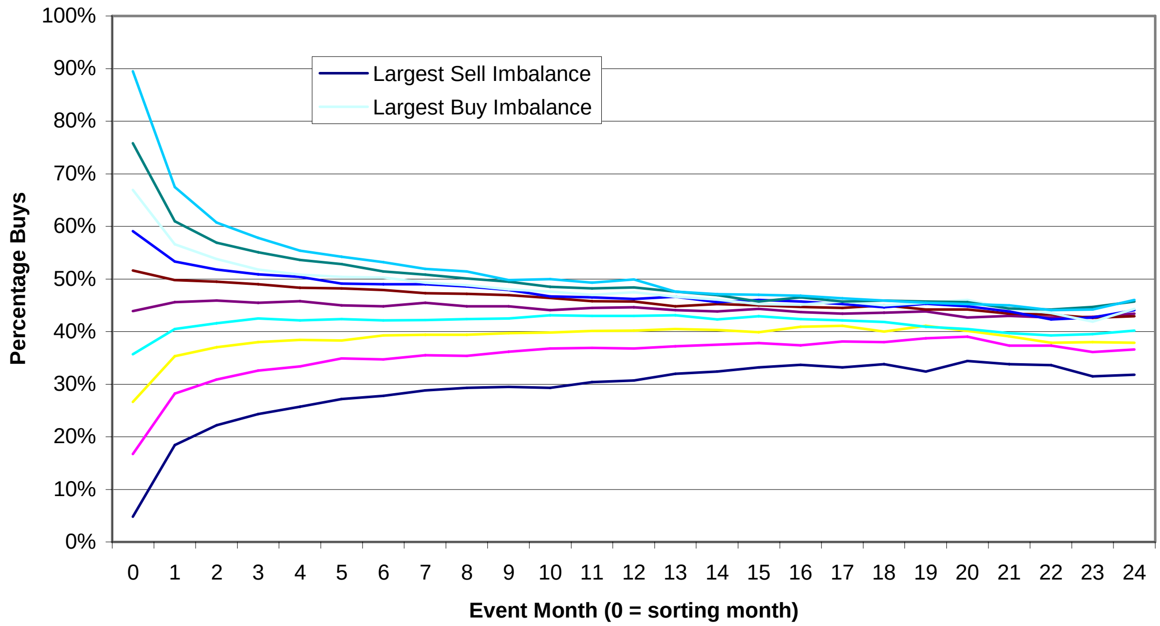

Figure 2b. Large Retail Broker, 1997-1999.

Figure 3: Percentage Buys in Event Time for Extreme Deciles of Order Imbalance by Firm Size

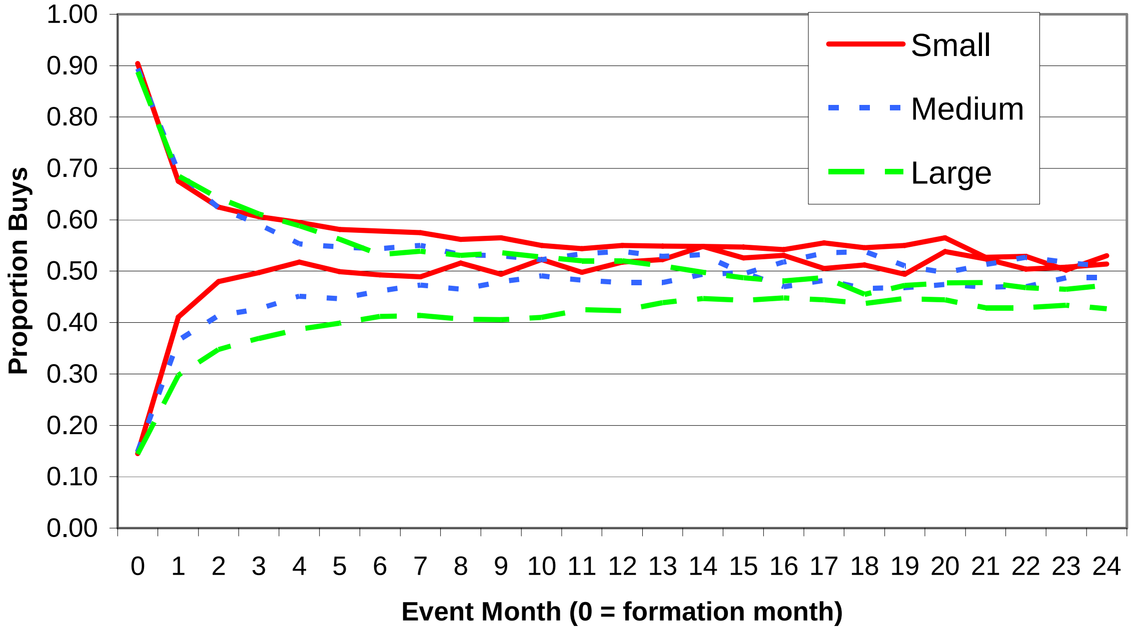

Figure 3a: Large Discount Broker, 1991-1996

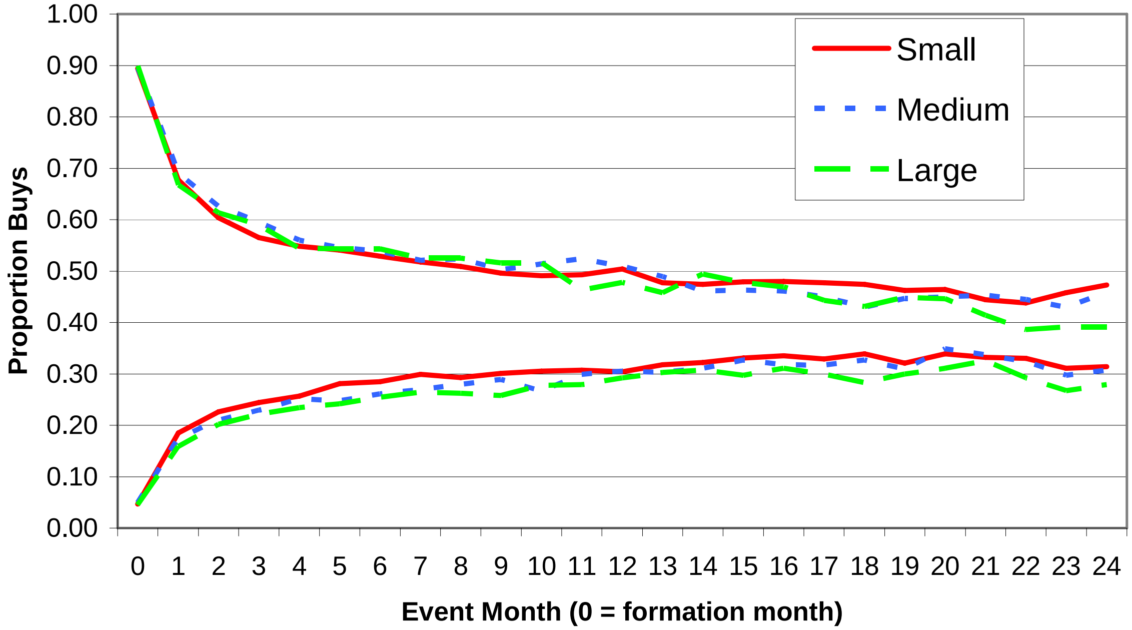

Figure 3b: Large Retail Broker, 1997-1999

Figure 4: Cumulative Market-Adjusted Returns around Purchases and Sales in Event Time

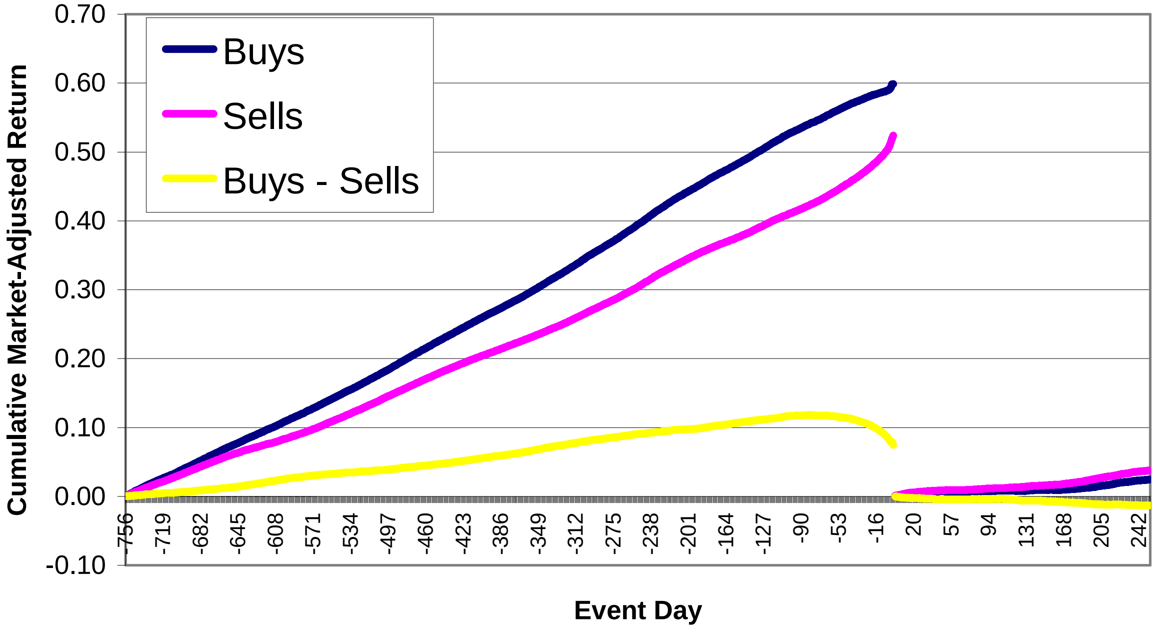

Figure 4a: Large Discount Broker, 1991-1996.

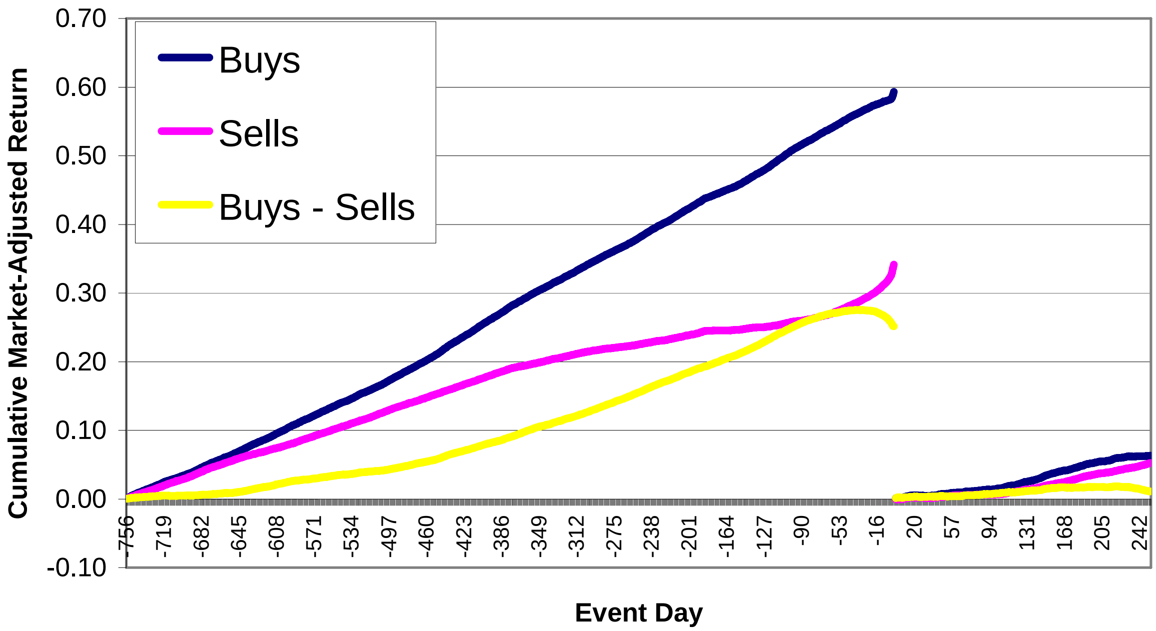

Figure 4b: Large Retail Broker, 1997-1999.