Systematic Noise

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Abstract

Several authors have suggested that the biases and sentiment of individual investors affect asset prices. For this to be true, the preference for buying some stocks while selling others must be shared by individual investors; we find this to be the case. 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 several 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 additional analyses, we present four stylized facts about the trading of individual investors: (1) they buy stocks with strong past returns; (2) they *also* sell stocks with strong past returns (though the relation is weaker than that for buying); (3) their buying is more concentrated in fewer stocks than selling; and (4) they are net buyers of stocks with unusually high trading volume. We argue that a combination of the disposition effect, the representativeness heuristic, and limited attention are the most plausible drivers of the coordinated trading that we document.

In his 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 does 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), (2002a)); 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).

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 & Venezia (2001); Grinblatt and Keloharju (2001); Dhar and Zhu, (2002)). They also sell stocks with recent gains (Odean (1999), Grinblatt and Kelharju (2001)). 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 (2002)). Investors tend to buy stocks that catch their attention (Barber and Odean (2002b)). And investors tend to underdiversify in their stock portfolios (Lewellen, Schlarbaum, and Lease (1974), Barber and Odean (2000), Goetzmann and Kumar (2002)) and in their retirement accounts (Benartzi and Thaler (2001), Benartzi, (2002)).[1]

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. 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 overpriced security and the substitute will converge. If, however, no perfect substitute exists or if 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 who's cost of carrying a short position is high.

[1] Other related work includes Kumar (2003) who analyzes the trading patterns of individual investors across style categories, Kumar and Lee (2002) 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, and Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2003) who develop a measure of investor sentiment using daily mutual fund flow data.

While it is difficult to prove that a particular stock, or even the entire market, is priced correctly or incorrectly relative to fundamentals, recent empirical studies document instances of stocks being mispriced relative to their substitutes. Mitchell, Pulvino, and Stafford (2002) examine 82 cases where the market value of a company was less than the market value of its ownership share in a publicly traded subsidiary. Similarly, Lamont and Thaler (2002) look at equity carve-outs in which the market value of the parent company's shares in the publicly traded carve-out exceeds the market value of the parent company itself. If informed traders are unable to fully reconcile the prices of stocks that are close substitutes, it seems likely that they also unable fully reconcile stock prices and fundamentals.

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 retail broker. Our main empirical results are quite consistent across the two datasets and can be summarized as follows. First, using several different methods, we find strong evidence of systematic trading 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.

Second, 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 in month *t* are much more likely to be purchased in subsequent months than stocks sold in month *t*. This persistence extends beyond one year, though it dissipates over time.

Naturally, these results raise the following question: What are the primary factors that coordinate the trades of individual investors? To answer this question, we separately analyze buying and selling activity. We argue that the primary factors that coordinate the purchase decisions of individual investors are attention and the overextrapolation of past returns – one manifestation of the Kahneman and Tversky's representativeness heuristic. Our empirical results provide strong evidence that individual investors are net buyers of attention-grabbing stocks and prefer to buy stocks with strong past returns. Buying is also consistently more concentrated in fewer stocks than selling, indicating the forces that coordinate buying are stronger than the forces that coordinate selling.

We argue the primary factor that coordinates selling decisions is the disposition effect – the tendency to sell winners while holding losers. Consistent with this conclusion, we document individual investors prefer to sell stocks with *strong* past returns. The disposition effect is one prediction of Kahneman and Tversky's prospect theory. Under prospect theory, people value investments relative to a reference point. The valuation of gains and losses is also asymmetric; the joy of a gain is less than the pain of a similar size loss. When selling a stock, investors have a natural reference point – their purchase price. In contrast, when buying a stock, there is no natural reference point. Thus, the disposition effect applies to selling, but not buying. If selling were the flip side of buying, we would expect selling to be concentrated in attention-grabbing stocks with poor past returns. However, attention is less of a problem for selling, since investors tend to hold few individual stocks and rarely sell short. And, for sale decision, the overextrapolation of past returns is more than offset by a countervailing factor – the disposition effect, which does not exist for buying.

In the next section, we describe the factors that might coordinate the trading of individual investors and develop testable hypotheses. We describe the data and our empirical methods in Section II and present results in Section III. In section IV, we discuss the implications of our empirical results and their relation to the institutional herding literature.

I. Hypothesis Development

In this section, we outline the factors that might reasonably influence the trades of individual investors. We start from first principles – standard asset pricing models that yield strong normative predictions about optimal portfolios. We then consider additional factors that might influence trade.

The Capital Asset Pricing Model (CAPM) provides a simple and powerful description of optimal investor behavior. In the CAPM world, investors own some combination of the market portfolio and a riskfree asset. Of course, investors may face liquidity shocks, which they will meet by selling (in the case of negative shocks) or buying (in the case of positive shocks). However, in this simple view of the world, investors will merely alter the size, but not the composition, of their portfolio; buying (or selling) is proportionate to the market capitalization of individual stocks within the market portfolio.

The Aribitrage Pricing Theory provides a multifactor view of the world, where investors optimally hold well-diversified portfolios. In this world, investors may optimally hold a portfolio that differs from the market. In contrast to the CAPM, when faced with liquidity shocks, individual investors will no longer buy (or sell) in proportion to the market capitalization of individual stocks within the market portfolio, but rather in proportion to the market capitalization of individual stocks within their well-diversified portfolio.

For concreteness, assume firm size is a proxy for a latent risk factor (Berk (1995)). Investors might optimally hold well-diversified portfolios of small (or large) stocks. Assume there are N investors who each choose efficient combinations of the big (B) and small (S) stock portfolio. Of the N investors, k experience a positive liquidity shock, while the remaining investors (N-k) experience a negative liquidity shock. Those investors who experience a positive liquidity shock will buy both the small and large portfolio in proportion to their current holdings so as to maintain their revealed factor risk preference. Those who experience a negative liquidity shock will sell both. Thus, there will be N trades in B and S, k purchases of B and S, and N-k sales of both B and S. The fraction of trades that are buys will be k/N for both B and S. In short, even in a multifactor risk setting (such as the APT) with liquidity shocks the fraction of trades that are buys will be similar across stocks.

The main testable hypothesis that emanates from this analysis is the percentage of trades that are purchases will be independent across stocks. However, we are fully aware that this is an extremely simplified view of the world. In the remainder of this section, and the main focus of our paper, is to identify the primary factors that might coordinate trades across investors.

I.A. Changing Risk Preferences

Assume investors' risk preferences change over time. For example, at times investors might be more willing to bear the risk associated with small stocks. Accordingly, they will sell some of their large stocks and buy small stocks. Extend the simple framework that we developed previously. Of the N investors, assume that k choose to increase their allocation to S, while N-k choose to increase their allocation to B. In this setting, we will observe N trades in B and S (as before). However, the fraction of trades that are purchases will be k/N for S and (N-k)/N for B. Thus, the fraction of trades that are buys will differ across stocks. Note, however, that the fraction of trades that are buys will be similar across big stocks ((N-k)/N) and across small stocks (k/N); that is, within a homogeneous risk class, the fraction of trades that are buys will be similar. Thus, if changing risk preferences coordinate trades, we will observe variation in the fraction of trades that are buys across different risk class, but not within a particular risk class.

I.B. Rebalancing

Even a well-diversified portfolio can, at times, become poorly diversified. For example, an investor may hold a portfolio of many stocks and bear negligible idiosyncratic risk. However, if she is fortunate enough to have one stock in her portfolio perform exceptionally well, that stock may become an uncomfortably large portion of her portfolio and leave her with a poorly diversified portfolio. This investor might reasonably sell part, but not all, of her appreciated stock to rebalance her portfolio. Transaction costs alone will discourage an investor from a complete sale of the appreciated security. If held in a taxable account, a complete sale will also unnecessarily accelerate the recognition of capital gains.

In summary, rebalancing will coordinate sales, since stocks with strong past returns are more likely to be sold for rebalancing purposes. However, the proceeds of the sale can be invested in any number of stocks. Thus, purchases will be spread over many stocks. The rebalancing hypothesis yields several testable implications. If rebalancing is the primary force that coordinates trades, sales will be concentrated in stocks with strong past returns, and sales will be more concentrated than purchases. In addition, partial sales, the most likely candidates for a rebalancing trade, will be more strongly related to past returns than complete sales.

I.C. The Disposition Effect

The tendency to hold losers and sell winners has been labeled the disposition effect by Shefrin and Statman (1985). The disposition effect is one implication of extending Kahneman and Tversky's (1979) prospect theory to investments. Under prospect theory, people behave as if maximizing an "S"-shaped value function. This value function is similar to a standard utility function except that it is defined on gains and losses rather than levels of wealth. The function is concave in the domain of gains and convex in the domain of losses. It is also steeper for losses than for gains, which implies that people are generally risk averse. In this framework, investors with liquidity needs are more likely to sell stocks that have gone up rather than down.

Many recent studies document that investors prefer to sell winners rather than losers. This is the case for individual stocks (Shefrin and Statman (1985), Odean (1999), and Barber and Odean (2002a)), residential housing (Genesove and Mayer (1999)), company stock options (Heath, Huddart, and Lang (1999)), and futures (Locke and Mann (2000)). It is also true for Israeli investors (Shapira and Venezia (2001)), Finnish Investors (Grinblatt and Keloharju (2001)), and Taiwanese investors (Barber, Lee, Liu, and Odean (2003)).

The disposition effect will coordinate sales and yields empirical predictions that are very similar to the rebalancing hypothesis. If the disposition effect is the primary force that coordinates trades, sales will be concentrated in stocks with strong past returns, and sales will be more concentrated than purchases. However, in contrast to the rebalancing hypothesis, the disposition effect will apply equally to partial and complete sales of stock.

I.D. Tax-Loss Selling

Investors might reasonably choose to sell their losing investments so as to harvest losses. The losses can be used to offset realized capital gains or, to a limited extent, ordinary income. This tax-loss selling can coordinate sales. In contrast to the rebalancing and disposition effect hypotheses, if tax-loss selling is the primary force that coordinates trades, sales will be concentrated in stocks with losses (rather than stocks with strong past returns). The rebalancing, disposition effect, and tax-loss selling hypotheses all predict sales will be more concentrated than purchases.

I.E. Information

If individual investors possess superior information (or analogously superior ability to interpret publicly available information), they will buy undervalued stocks and sell overvalued stocks. Thus, their trades would be coordinated. The information hypothesis yields the unique prediction that the stocks collectively bought by individuals will earn superior risk-adjusted returns, while those collectively sold will earn poor risk-adjusted returns.

Alternatively, individual investors might provide liquidity in the form of unmonitored limit orders to informed investors (presumably institutions). Many individual investors who place limit orders are unable to monitor these orders throughout the day. If institutions drive prices down one day by actively selling, the buy limit orders of individual investors are likely to systematically execute. Similarly, if institutions drive prices up by buying, the sell limit orders of individuals will execute. In this setting, the trading of individual investors would be coordinated not by their actions (i.e., market orders), but their inaction (poorly monitored limit orders). If unmonitored limit orders is the primary factor that coordinates the trading of individual investors, their limit order trades would be coordinated, but their market orders would not be coordinated.

I.F. Representativeness

People often make decisions using a representativeness heuristic. They evaluate a probability of an uncertain event or sample "by the degree to which it is (i) similar to its parent population and (ii) reflects the salient features of the process by which it is generated" (Tversky and Kahneman (1974, p.33). For example, when people are given a detailed description of an individual's personality that confirms their stereotypes of a particular profession, they overestimate the probability that the individual belongs to that profession.

An important aspect of the representativeness heuristic is the strong desire to see patterns where there are none (Tversky and Kahneman (1974)). For example, DeBondt (1993) uses experimental evidence and surveys to document investors extrapolate past price trends. In one experiment, subjects are asked to forecast future prices after being shown past prices. He also analyzes a sample of regular forecasts of the Dow Jones Index from a survey of American Association of Individual Investor members. In both settings, investors expect higher future prices following past price increases.

Several studies acknowledge the potential importance of the representativeness heuristic in financial markets. DeBondt and Thaler (1985, 1987) argue the representativeness heuristic causes investors to overweight the importance of past returns when valuing stocks. Consequently, investors overvalue stocks with strong past returns and undervalue stocks with poor past returns. They analyze the returns of long-term winners and losers to test this overreaction hypothesis.[2] 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.

The representativeness heuristic predicts that investors will overweight past returns when valuing stocks. Stock with strong past returns are viewed as representative of winning investments, while stocks with poor past returns are viewed as representative of losing investments. If the representativeness heuristic is the primary force that coordinates trades, purchases will be concentrated in stocks with strong past returns, while sales will be concentrated in stocks with poor past returns.

I.G. Attention

Barber and Odean (2002b) hypothesize that investors disproportionately buy, rather than sell, attention-grabbing stocks. When buying a stock, investors face a formidable search problem; there are thousands of 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

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[2] To test this hypothesis, they analyze the returns of long-term (36-month) winner and (36-month) loser portfolios. Consistent with the overreaction hypothesis, they document the long-term loser portfolios subsequently outperforms the long-term winner portfolio. Subsequent research has documented that this return differential is captured by the now popular value-growth factors (see Fama and French (1996)), though whether the value-growth factor is a proxy for risk or investor overreaction remains hotly debated (see Fama and French (1992, 1993) and Lakonishok, Shleifer, and Vishny (1994) for the two sides of this argument).

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 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, many individual investors hold relatively few individual common stocks in their portfolio. Second, most individual investors only sell stocks that they already own, that is, they don't sell short. Investors can, one by one, consider the merits—both economic and emotional—of selling each stock they own. Thus, the buying behavior of individual investors is more heavily influenced by attention than is their selling behavior.

Attention-based trading will coordinate trades. If attention is the primary factor that coordinates trades, purchases will be more concentrated than sales in attention-grabbing stocks. In general, buying will be more concentrated than selling.

I.H. Summary

The different theories advanced are not mutually exclusive. Thus, our goal is to identify testable implications that will ultimately allow us to identify the primary forces that coordinate trades. We summarize the testable hypotheses that emanate from above discussion.

H1: The trading decisions of individual investors are independent across stocks

Though individual investors may be net buyers of stock in one period and net sellers in another period, they should display no particular preference for one stock over another.

H2: Selling and buying are equally concentrated.

The rebalancing, disposition effect, and tax loss hypotheses all predict selling, but not buying, is coordinated. If any of these hypotheses are the primary explanation for coordinated trading, selling would be more concentrated than buying. In contrast, the attention hypothesis predicts buying will be more concentrated than selling. (The information, representativeness, and changing risk preferences hypotheses yield no predictions about the relative concentration of buying and selling.)

H3: Trading is coordinated similarly across risk classes and within a particular risk class.

The changing risk preference hypothesis predicts that investor trades will be correlated across, but not within, a risk class. The remaining hypotheses predict trading would be coordinated similarly across risk classes *and* within a particular risk class.

H4: Individual investor limit orders and market orders are similarly coordinated.

If institutions actively pick off the unmonitored limit orders of individuals, we will observe a greater coordination of trade in limit, rather than market, orders.

H5a: Buying intensity is independent of past returns.

H5b: Selling intensity is independent of past returns.

Several hypotheses yield predictions about the relation between trading and past returns. The rebalancing and disposition effect hypotheses predict investors will sell stocks with strong past returns. The tax hypothesis predicts investors are more likely to sells stocks with poor past returns (i.e., losers). The representativeness hypothesis predicts investors will buy stocks with strong past returns, while selling stocks with poor past returns.

H6: Buying intensity is independent of attention-grabbing events

The attention hypothesis predicts that investors will be net buyers of stocks that experience attention-grabbing events. The remaining hypotheses are silent on the relation between attention and buying intensity.

H7: Sales of complete and partial positions are related to past returns in a similar fashion.

The rebalancing hypothesis predicts that investors will sell a portion, but not the complete holding, of an investment when it becomes a large part of their investment portfolio. Thus, partial sales will be high when past returns on a stock are high, but complete sales will be unaffected by strong past returns. In contrast, the disposition effect predicts that both complete and partial sales are positively related to past returns.

H8: Stocks that are heavily bought earn risk-adjusted returns that are equal to stocks that are heavily sold.

The information hypothesis predicts stocks that are heavily bought will outperform stocks that are heavily sold.

II. Data and Methods

II.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 value of buys and sells is 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 for the discount broker, 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.) Since we will imprecisely estimate buying intensity for stocks with few trades during a month, we delete from our analysis stocks with less 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.

II.B. Distribution Analysis

We employ three approaches to test our main hypothesis (H1) – that trading decisions are independent. 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}.

II.C. Correlation Analysis

II.C.1. Contemporaneous Correlation

Our second approach to test for independence of 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.[3] 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.

II.C.2. Temporal Correlation

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 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 $t+L$.

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[3] 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.

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.D. Concentration Measures

Several of the hypotheses discussed yield predictions about the concentration of buying relative to selling. We use a Herfindahl index to separately measure the concentration of buying and selling. Define b_{it} as the number of buys in stock i in month t. For month t, we calculate the following concentration measure for buys:

$$CB_t = \sum_{i=1}^{N} \left(\frac{b_{it}}{\sum_{i=1}^{N} b_{it}} \right)^2 . \tag{2}$$

As buying becomes more concentrated in fewer stocks, the concentration measure will increase. There is a similar calculation for selling. Thus, for the discount broker, we obtain a time-series of 71 monthly buy (and sell) concentration measures. For the retail broker, we obtain a time series of 30 monthly concentration measures.

We also analyze the monthly proportion of buys in the fifty stocks with the most purchases and the proportion of sells in the fifty stocks with the most sales. To test the null hypothesis that the concentration of buying and selling is equal, we calculate the mean difference between the buying and selling concentration measures. Statistical tests are based on the time-series standard deviation of the difference in the concentration measures.

II.E. Performance

To evaluate the performance and style characteristics of stocks that are heavily bought (or sold) by individuals, we construct calendar-time portfolios as follows. First, in each month we partition stocks into deciles on the basis of buying intensity. Second, we construct value-weighted calendar-time portfolios of stocks within each decile assuming a holding period of one year. (Since deciles are formed monthly and we assume a holding period of one year, a particular stock can appear in the portfolio more than once, but no more than twelve times.)

Ultimately, for each dataset, we calculate ten time-series of monthly returns – one for each decile of buying intensity. For the large discount broker data, which spans the period January 1991 to November 1996, the analysis yields an 82-month time-series of returns for the period February 1991 to November 1997. For the large retail broker data, which spans the period January 1997 to June 1999, the analysis yields a 41-month time-series of returns for the period February 1997 to June 2000.

To analyze the performance and style characteristics of these portfolios, we employ a four-factor model that includes market, size, value, and momentum factors (Carhart (1997)). For example, to evaluate the return performance of a particular decile (R_{pt}) we estimate the following monthly time-series regression:

$$\left(R_{pt} - R_{ft}\right) = \alpha_j + \beta_j\left(R_{mt} - R_{ft}\right) + s_j SMB_t + h_j VMG_t + m_j WML_t + \varepsilon_{jt} \ , \qquad (3)$$

where R_{ft} is the monthly return on T-Bills,[4] 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.[5] 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*

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

[5] 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.

denotes parameter estimates and error terms from regression *j*, where we estimate ten regressions – one for each decile.

These regressions allow us to draw inferences about the style characteristics of stock heavily purchased (or sold) by individuals. Portfolios with above-average market risk have betas greater than one, $\beta_j > 1$. Portfolios with a tilt toward small stocks relative to a value-weighted market index have size coefficients greater than zero, $s_j > 0$. Similarly, portfolios with a relative value tilt will have a value coefficient greater than zero ($h_j > 0$), while portfolios with a relative winner tilt have a momentum coefficient greater than zero ($m_j > 0$).

To measure performance, we test the null hypothesis that the intercept from the four-factor regression is equal to zero. For the sake of completeness, we also present market-adjusted returns (using a value-weighted index of NYSE/ASE/Nasdaq stocks as our market benchmark), intercept tests from the Capital Asset Pricing Model (i.e., Jensen's alpha), and intercept tests from the Fama-French three-factor model (which includes only the market, size, and value factors).

III. Results

III.A. Independence Results

III.A.1. 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 our first hypothesis (H1). The trading decisions of individual investors are not independent.

III.A.2. 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. Each line in the 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 1a). 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.

III.B. Concentration Results

Our analysis of the concentration measures of buying and selling provide strong evidence that buying is more concentrated than selling. For the discount broker, the average monthly buy concentration (0.0039) is 63 percent greater than the average monthly sell concentration (0.0024). For the retail broker, the average buy concentration (0.0092) is nearly three times the average sell concentration (0.0031). The differences for both the discount and retail broker are reliably positive ($p<0.001$). Furthermore, the buy concentration exceeds the sell concentration measure in 66 of 71 months for the discount broker and all 30 months for the retail broker.

For the large discount broker, on average, the fifty stocks with the most purchases represent 31 percent of all buys, while the fifty stocks with the most sales represent 26 percent of all sales. For the large retail broker, the percentages are 44 and 29, respectively. Using either concentration measure, we are able to comfortably reject the null hypothesis that buying and selling are equally concentrated. The buying behavior of individual investors is more concentrated than their selling behavior. We are able to comfortable reject the null hypothesis that buying and selling is equally concentrated (H2).

III.C. Results by Firm Size

We calculate the persistence of buying intensity separately for small, medium, and large stocks. We do so for two reasons. First, the sorts on size test the robustness of our results. Second, firm size is a reasonable proxy for risk. Using firm size as a proxy for risk has strong theoretical (Berk (1995)) and empirical foundations (Banz (1981)). With a reasonable risk proxy, we are able to empirically test the hypothesis that changing risk preferences are the primary factor that coordinates trade.

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 are fully aware that these bright-line classifications on firm size are crude measures of risk. Thus, we do not anticipate (or find) that the percentage buys is independently distributed within a size class. However, if changing risk preferences is the primary factor that coordinates trade, we do expect the cross-sectional variation in percentage buys would be less within a size class, rather than across all stocks.

To formally test hypothesis 3, 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. If changing risk preferences are the primary explanation for coordinate trading, we expect that the herding measure for all stocks will be greater than the herding measure within a particular size class. The results of this analysis are presented in the last three rows of table 2. For the retail broker, the herding measures are very similar across all stocks and within each size class; none of the herding measures within a size class are reliably different from the herding measure for all stocks. 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 (the only evidence that is consistent with the predictions of the changing risk preference hypothesis). In summary, there is, at best, limited evidence that changing risk preferences explain the coordinate trading that we document.

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 the 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 this 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.[6]

[6] Kumar (2003) 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.

III.D. Limit vs. Market Orders

Is the contemporaneous correlation in the buying and selling of individual investors driven by individuals making correlated trading decisions or is it the result of individual investors reacting passively, via unmonitored limit orders, to the trading demands of institutional investors? To formally test this hypothesis (H4) 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 that reported in Table 3. 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 that reported in Table 3. The temporal auto-correlations of buying intensity for both groups are also qualitatively similar to that 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.

III.E. Cross-Sectional Regressions

Several of the hypotheses that we discuss yield predictions about the relation between trading and past returns. The rebalancing and disposition effect hypotheses

[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.

predict investors will sell stocks with strong past returns. The tax hypothesis predicts investors are more likely to sells stocks with poor past returns (i.e., losers). The representativeness hypothesis predicts investors will buy stocks with strong past returns, while selling stocks with poor past returns.

To begin, 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. Stocks sold also outperform the market, but not by such a large margin.

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. We further document these relations in a cross-sectional regression approach later in this section.

The attention hypothesis predicts that individual investors will be net buyers of attention-grabbing stocks. One measure of the extent to which a stock grabs investors' attention is its abnormal trading volume. Imagine standing on a street and observing a large crowd gathered at one end of the street and nobody stopped at the other end. You don't know why the crowd has gathered, maybe to watch street performers, maybe to help an old man who had a heart attack. You do know that an attention-grabbing event is taking place on the end of the street where the crowd has gathered not the end without a crowd. Similarly when, as researchers, we observe abnormal trading volume in a stock, we know that something has happened to grab investors' attention—though we may not know what that something is. Though abnormal trading volume, per se, does not capture attention, it serves as a proxy for unobserved attention-grabbing events. Clearly the number of buys and sells for a stock will be equal on all days – even those days with high volume. However, we expect the group with more limited attention – individual investors – will be net buyers on high-attention (i.e., unusually high volume) days. We measure abnormal trading volume as the dollar volume for stock *i* in month *t* scaled by the mean dollar volume for stock *i* in months *t-13* to *t-2*.

A simple univariate analysis provides strong support for the attention hypothesis. We calculate the mean level of abnormal volume for each of the deciles that we construct based on buying intensity. The results of this analysis are presented in table 4. Not surprisingly, abnormal volume is high for each decile, since we condition on a minimum of 10 trades in each stock. However, for both datasets, abnormal volume is greatest in those stocks that are heavily purchased. We also analyze share turnover – the monthly volume of shares traded dvided by outstanding shares. Again, share turnover is quite high for all deciles – ranging from 8 to 17 percent monthly turnover. However, for both datasets, share turnover is greatest in those stocks that are heavily purchased.

To augment our univariate analyses, we estimate the following cross-sectional regression:

$$PB_{it} = a_t + \sum_{j=1}^{12} b_{jt} R_{q-j} + c_t AV_{it} + d_t PB_{i,t-1} + \varepsilon_{it}\,, \tag{4}$$

where PB_{it} is the proportion of trades that are buys in stock *i* in month *t*, R_{t-j} is the log-return for stock *i* in quarter *t-j* (e.g., in November 1991, quarter *t-1* would span the three months ending in October 1991), AV_{it} is the log of abnormal volume for stock in month *t*, and $PB_{i,t-1}$ is the lagged proportion of buys. We include the lagged dependent variable to account for the previously documented time-series dependence in the proportion of buys. Since the proportion of buys is estimated more precisely for stocks with many trades, we estimate a weighted least square regression in each month, where the weights are equal to the square root of the number of trades in stock *i*. We exclude stocks with fewer than ten trades. Statistical tests are based on the mean coefficient estimates across months (70 months for the discount broker and 29 months for the retail broker).

To gain better insights into the determinants of trading, we separately analyze buying and selling. Specifically, we estimate the following cross-sectional regressions in each month:

$$\frac{B_{it}}{P_{it}} = a_t^b + \sum_{j=1}^{12} b_{jt}^b R_{q-j} + d_t^b \frac{B_{it}}{P_{it}} + \varepsilon_{it}^b, \tag{5a}$$

$$\frac{S_{it}}{P_{it}} = a_t^s + \sum_{j=1}^{12} b_{jt}^s R_{q-j} + d_t^s \frac{S_{it}}{P_{it}} + \varepsilon_{it}^s, \tag{5b}$$

where B_{it}/P_{it} is the number of buys for stock *i* in month *t* scaled by the number of beginning-of-month positions in the stock, and S_{it}/P_{it} is an analogous variable constructed using the number of sales. In this analysis, we limit our observations to stocks with a minimum of 100 positions across all households (but include stocks with no trades). These regressions measure the intensity of buying (or selling) relative to positions held. We also estimate a difference regression where $(B_{it} - S_{it})/P_{it}$ is the dependent variable in the regression. In the buy and sell regressions, we omit abnormal volume as an independent variable, since it is tautological that buying and selling will increase when volume increases. However, we include abnormal volume in the difference regression; it is not obvious that individual investor buying and selling will differ for stocks with unusually large volume. These regressions are estimated in 69 months for the large discount broker and 16 months for the large retail broker (since we only have positions for the large retail broker from January 1998 through June 1999).

The results of this analysis are presented in Table 5. Focus first on the regressions that use the proportion buys as the independent variable (column 2 for the discount broker and column 6 for the retail broker). For both the discount and retail broker, there is a reliable *negative* relation between percentage buys and quarter *t-1* return. For both datasets, this negative relation turns positive in quarter *t-4* through *t-10*, though the importance of returns at greater lags diminishes. For both datasets, there is a reliably positive relation between percentage buys and abnormal volume.

The regressions that separately analyze buying and selling shed more light on these relations. The results of this analysis can be summarized as follows. Individual investors buy stocks with strong past returns. This relation is initially weak, peaks in quarter *t-4*, and dissipates slowly thereafter. Individual investors also sell stocks with strong past returns. Initially, the relation is strong, peaks in quarter *t-1*, and dissipates more quickly than the relation for buying. (The statistical significance of results based on data from the large retail broker are generally weaker, since we are able to estimate the regressions in only 16 months as opposed to 69 months for the large discount broker.) Thus, though investors prefer to buy *and* sell stocks with strong recent (quarter *t-1*) returns, they are net sellers of these stocks. Though investors prefer to buy *and* sell stocks with strong distant returns (quarters *t-4* through *t-10*), they are net buyers of these stocks.

In summary, we are able to reject the null hypothesis that buying and selling are independent of past returns (H5a and H5b). Though the time-series properties of the relations differ, individual investors prefer to buy *and* sell stocks with strong past returns. In addition, we are able to reject the hypothesis that buying decisions are independent of attention-grabbing events (H6); individual investors are net buyers of stocks with abnormally high volume.

III.F. Complete vs. Partial Sales

Both the disposition effect and rebalancing hypotheses predict a positive relation between selling and past return performance. To differentiate these two explanations of the observed relation, we separately analyze complete and partial sales of a security. As previously discussed, if rebalancing is the primary motivation for selling, an investor would generally only sell part, but not all, of their holding in the appreciated asset.

First, we identify complete and partial sales in both datasets. In both datasets, less than 25 percent of sales are partial sales. We use these data to estimate the regression of equation 5b (columns 4 and 8 of table 5), but redefine the numerator of the dependent variable as, alternately, the number of complete sales of stock *i* in month *t* or the number of partial sales. If rebalancing is the primary motivation behind the selling activity that we observe, we would expect a stronger relation between past returns and partial sales (the likely candidates for rebalancing trades) than between past returns and complete sales.

The results of these regressions yield results that are qualitatively similar to those presented in table 5 for *both* complete and partial sales. More importantly, there is no evidence that partial sales are more strongly related to past returns than complete sales. For the large discount broker, all coefficient estimates on past returns are greater when the dependent variable is based on complete, rather than partial, sales (though most of the differences are not reliably positive). For the large retail broker, all but one (quarter *t-2* yields an insignificant negative coefficient) are greater when the dependent variable is based on complete, rather than partial, sales. We are unable to reject the null hypothesis that complete and partial sales are related to past returns in a similar fashion (H7). These results indicate rebalancing is not the primary motivation underlying the selling behavior that we observe.

III.G. Performance

Do stocks heavily bought by individuals subsequently outperform stocks heavily sold by individuals? To formally test the null hypothesis of equal performance (H8), we analyze the returns on stocks heavily bought versus those heavily sold. There is no convincing evidence that stocks heavily purchased outperform those heavily sold. The evidence used to answer this question is presented in Table 6, where we present various abnormal return measures for the deciles formed on buying intensity. For the large discount broker, stocks heavily bought (i.e., high buying intensity) underperformed stocks heavily sold (i.e., low buying intensity) by 27 basis points per month, though not reliably so. Furthermore, the return difference varies depending on the asset pricing model employed (see columns three through six) and is never reliably different from zero. For the large retail broker (panel B), stocks heavily bought *outperformed* stocks heavily sold by 64 basis points per month, though not reliably so. Again, the return difference varies depending on the asset pricing model employed and is never reliably different from zero.[8]

IV. Institutional Herding

Our study contrasts with the institutional herding literature. Devenow and Welch (1996) point out that while herding could be defined as any behavior 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 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

[8] For several reasons, these results are not proof that investors at the retail brokerage or the discount brokerage earn better expected returns than each other: 1) None of the abnormal return measures are statistically different from zero. 2) There are different numbers of trades, though similar numbers of stocks, in the deciles. 3) Which group of investors earns higher abnormal returns depends on the risk model used. 4) Returns for the two brokerages are measured for periods in which the market behaved very differently. 5) These are gross returns that do not factor in trading costs such as commissions.

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 are 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 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). 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).

And 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.[9] Furthermore, broker advice cannot explain the long persistence in auto-correlated buying intensity, unless brokers are remarkably unwavering in their advice.

Finally, 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.

V. Discussion

What are the main factors that coordinate the trading of individual investors? Before beginning our discussion, it is useful to summarize our main empirical findings. Though one might quibble with the interpretation of these findings, we believe, at a minimum, we have convincingly established the following stylized facts about the trading of individual investors.

(1) Individual investors buy stocks with strong past returns,

(2) Individual investors also sell stocks with strong past returns; this relation is stronger than that for buys at short horizons (one to two quarters), but weaker at long horizons (up to 12 quarters),

(3) Their buying is more concentrated in fewer stocks than selling, and

(4) They are net buyers of stocks with unusually high trading volume.

At the outset, we discuss several possible mechanisms that might coordinate trade. Tax-loss selling and rebalancing might coordinate sales. Changing risk preferences or superior information can coordinate trade. Institutions might "pick off" the unmonitored limit orders of naïve individual investors. We are certain some trading can

[9] 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.

be explained by each of these factors. However, our auxiliary analyses indicate these factors are not the main drivers that coordinate trade.

We believe two factors best explain the buying patterns that we observe: the representativeness heuristic and attention. Investors likely buy stocks with strong past returns because these stocks are viewed as representative of good investments. Investors simply expect good performance to repeat. Furthermore, investors are net buyers of attention-grabbing stocks (those with unusually high volume). In contrast to selling, when investors choose from only a handful of stocks that they own, the purchase decision presents a formidable search problem, since there are thousands of stocks from which to choose. For most individual investors, attention is a scarce resource; it is only natural that they tend to be net buyers of stocks that grab their attention. This factor alone would cause buying to be more concentrated than selling.

In contrast to buying, the selling decisions of individual investors is not predominantly influenced by the representativeness heuristic, which predicts investors would sell stocks with poor past returns. This is because, unlike buying, there is a powerful countervailing factor – the disposition effect or the tendency to avoid the regret associated with the sale of a losing investment. The existence of this countervailing factor leaves selling less concentrated than buying. Though we suspect individual investors are less optimistic about the future prospects of stocks with poor returns relative to those with strong past returns, it is difficult for them to come to terms with their losses. This regret avoidance mechanism wields a powerful influence over the selling decision.

It is somewhat inappropriate to characterize individual investors as contrarian or momentum investors, since they buy *and* sell stocks with strong past returns. Thus, individual investors are somewhat schizophrenic – momentum investors when it comes to buying, but contrarian when it comes to selling. Though this empirical result is extremely robust and at first puzzling, we suspect the lack of symmetry in these relations results from the fundamental difference in how investors view the purchase versus the sale decision.

VI. 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.

Auxiliary analyses establish four strong empirical regularities: (1) Individual investors buy stocks with strong past returns; (2) individual investors also sell stocks with strong past returns; this relation is stronger than that for buys at short horizons (one to two quarters), but weaker at long horizons (up to 12 quarters); (3) their buying is more concentrated in fewer stocks than selling; and (4) they are net buyers of stocks with unusually high trading volume.

Though many factors can coordinate trading (e.g., tax-loss selling, rebalancing, changing risk preference, or superior information), we argue our empirical results are primarily driven by three behavioral factors: the representativeness heuristic, limited attention, and the disposition effect. When buying, similar beliefs about performance persistence in individual stocks may lead investors to buy the same stocks – a manifestation of the representativeness heuristic. Investors may also buy the same stocks simply because those stocks catch their attention. In contrast, when selling, the extrapolation of past performance and attention play a secondary role. Attention is less of an issue for selling, since many investors hold few stocks. If investors solely extrapolated past performance, they would sell losers. However they don't do so. This is because, when selling, there is a powerful countervailing factor – the disposition effect – a desire to avoid the regret associated with the sale of a losing investment. Thus, investors sell winners rather than losers.

The influence of one individual investor on asset prices is negligible. For psychological biases to affect asset prices, these biases must cause many investors to do the same thing. This proves to be the case. The buying and selling decisions of individuals are highly correlated and they cumulate over time. 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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(Revision in progress – citations are incomplete)

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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	0.1242
	(<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.

Table 4: Trading Volume Measures for Deciles based on Monthly Buying Intensity

Deciles are formed on the basis of percentage buys each month. The characteristics of stocks in each decile are measured in the same month. Number of trades is the mean number of trades per stock within the database. Share turnover is volume divided by shares outstanding. Abnormal volume is dollar volume in month t divided by dollar volume in months t-12 to t-2. For each decile, means are calculated each month. The table presents the grand mean across months. Standard errors (in parentheses) are based on the time-series of monthly means using a Newey-West correction for serial dependence.

	Large Discount Broker: 1991-1996				Large Retail Broker: 1997-1999			
	% Buys	No. of Trades	Share Turnover (%)	Abn. Volume	% Buys	No. of Trades	Share Turnover (%)	Abn. Volume
Lo	14.4	23.9	10.77	1.53	7.1	44.8	8.43	1.39
			(0.30)	(0.06)			(0.22)	(0.06)
2	29.3	28.8	12.00	1.57	16.6	55.9	8.91	1.33
			(0.38)	(0.07)			(0.18)	(0.06)
3	38.6	29.7	12.39	1.56	26.5	61.4	9.94	1.31
			(0.48)	(0.06)			(0.31)	(0.08)
4	46.0	32.2	13.16	1.68	35.8	61.9	11.06	1.38
			(0.57)	(0.09)			(0.29)	(0.07)
5	52.5	32.8	14.43	1.94	44.0	73.3	12.27	1.46
			(0.71)	(0.10)			(0.41)	(0.09)
6	58.8	36.5	14.56	1.98	51.7	78.8	14.99	2.10
			(0.76)	(0.13)			(0.72)	(0.36)
7	64.6	37.3	15.34	2.39	59.4	98.6	16.36	2.27
			(0.76)	(0.32)			(1.08)	(0.37)
8	71.0	38.8	15.47	2.38	67.2	123.3	17.29	2.12
			(0.80)	(0.21)			(1.34)	(0.27)
9	78.4	39.4	16.44	2.40	76.1	154.0	17.02	2.01
			(0.91)	(0.21)			(0.89)	(0.26)
Hi	89.9	30.9	17.11	2.71	89.8	132.7	13.94	1.94
			(0.86)	(0.21)			(0.38)	(0.19)
Lo – Hi	-75.5	-7.0	-6.34	-1.18	-82.7	-87.9	-5.51	-0.54
			(0.82)	(0.19)			(0.51)	(0.14)

Table 5: Cross-Sectional Regressions of Buying and Selling Intensity

In each month, we regress the percentage buys on each stock on lagged quarterly returns over three years (Ret. Q-1 through Q-12), abnormal volume in the stock during the month, and one-month lagged percentage buys. The table reports the mean coefficient estimates across months. Test statistics (in parentheses) are based on the time series of coefficient estimates (70 months for the retail broker and 29 months for the discount broker). We also estimate regressions where the dependent variable is, alternately, the number of buys divided by the number of positions, the number of sells divided by number of positions, and the number of buys less sells divided by the number of positions.

	Large Discount Broker				Large Retail Broker			
	% Buys	B/Pos	S/Pos	(B-S) / Pos	% Buys	B/Pos	S/Pos	(B-S) / Pos
Intercept	0.273 (38.97)*	0.014 (16.91)*	0.014 (23.15)*	0.001 (1.01)	0.162 (36.59)	0.010 (12.68)*	0.015 (13.47)*	-0.006 (-7.57)*
Ret. Q-1	-0.121 (-15.17)*	0.005 (1.41)	0.015 (4.81)*	-0.039 (-13.46)*	-0.075 (-7.32)*	-0.004 (-0.99)	0.009 (2.18)*	-0.024 (-7.37)*
Ret. Q-2	-0.036 (-5.42)*	0.012 (4.07)*	0.009 (4.27)*	-0.010 (-3.64)*	0.013 (1.70)	0.006 (1.61)	0.001 (0.24)	-0.002 (-0.97)
Ret. Q-3	-0.002 (-0.24)	0.011 (3.60)*	0.006 (3.07)*	-0.001 (-0.42)	0.012 (1.78)	0.010 (2.42)*	0.006 (1.29)	-0.001 (-0.23)
Ret. Q-4	0.019 (2.96)*	0.019 (8.21)*	0.009 (3.82)*	0.009 (5.41)*	0.044 (6.23)*	0.013 (4.92)*	0.004 (1.52)	0.009 (3.51)*
Ret. Q-5	0.032 (4.92)*	0.015 (4.98)*	0.007 (3.22)*	0.011 (4.34)*	0.044 (5.13)*	0.009 (3.98)*	-0.001 (-0.34)	0.012 (4.95)*
Ret. Q-6	0.033 (4.38)*	0.012 (4.96)*	0.006 (2.39)*	0.012 (4.92)*	0.040 (8.54)*	0.008 (2.40)*	0.002 (0.87)	0.0007 (2.69)*
Ret. Q-7	0.025 (3.05)*	0.0131 (5.17)*	0.008 (3.36)*	0.009 (4.27)*	0.038 (5.06)*	0.006 (1.85)	0.001 (0.54)	0.007 (2.71)*
Ret. Q-8	0.022 (3.56)*	0.009 (4.97)*	0.006 (3.67)*	0.006 (3.30)*	0.020 (2.88)*	-0.0003 (-0.09)	0.001 (0.28)	-0.001 (-0.34)
Ret. Q-9	0.017 (2.40)*	0.008 (3.10)*	0.005 (2.60)*	0.007 (3.17)*	0.020 (3.37)*	0.002 (0.85)	-0.0001 (-0.04)	0.003 (1.82)
Ret. Q-10	0.021 (3.07)*	0.007 (2.34)*	0.002 (1.09)	0.008 (3.21)*	0.027 (5.38)*	0.001 (0.27)	-0.001 (-0.71)	0.004 (2.16)*
Ret. Q-11	0.014 (1.77)	0.007 (2.56)*	0.004 (1.75)	0.004 (1.79)	0.012 (1.81)	0.007 (2.41)*	0.004 (2.24)*	0.002 (1.21)
Ret. Q-12	0.013 (1.76)	0.006 (2.47)*	0.004 (1.63)	0.005 (1.93)	0.018 (2.53)*	0.004 (1.18)	0.001 (0.43)	0.004 (1.74)
Abn. Vol.	0.049 (16.33)*	---	---	0.016 (12.63)*	0.034 (9.09)*	---	---	0.009 (5.73)*
Lagged Dep. Var.	0.462 (8.97)*	0.529 (31.50)*	0.533 (26.89)*	0.353 (27.34)*	0.605 (63.47)*	0.447 (18.38)*	0.455 (12.31)*	0.315 (24.25)*

Table 6: Percentage Return Performance and Style Tilts of Portfolios Formed on the Basis of Monthly Order Imbalance

Value-Weighted portfolios are formed on the basis of percentage buys in each month. Securities are held in the portfolio for 12 months subsequent to portfolio formation. To evaluate the return performance of a particular decile (R_{pt}) we estimate the following monthly time-series regression:

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

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. We also present market-adjusted returns (using a value-weighted index of NYSE/ASE/Nasdaq stocks as our market benchmark), intercept tests from the Capital Asset Pricing Model (i.e., Jensen's alpha), and intercept tests from the Fama-French three-factor model (which includes only the market, size, and value factors). *t-statistics* are in parentheses.

	Large Discount Broker					Large Retail Broker				
	Raw	Market Adjusted	CAPM	Three-Factor	Four-Factor	Raw	Market Adjusted	CAPM	Three-Factor	Four-Factor
Lo	1.641	0.148	0.162	0.022	-0.023	1.033	-0.650	-0.333	-0.291	-0.237
		(1.06)	(1.08)	(0.16)	(-0.16)			(-0.99)	(-1.11)	(-0.89)
2	1.557	0.064	0.073	0.016	0.006	1.634	-0.049	0.243	0.253	0.342
		(0.57)	(0.61)	(0.15)	(0.05)			(0.66)	(1.03)	(1.41)
3	1.575	0.082	-0.011	0.013	0.051	1.644	-0.040	0.204	0.219	0.331
		(0.76)	(-0.10)	(0.12)	(0.48)			(0.84)	(1.12)	(1.83)
4	1.621	0.129	0.048	0.171	0.226	1.551	-0.133	0.084	0.077	0.241
		(1.24)	(0.44)	(1.83)	(2.38)			(0.27)	(0.34)	(1.25)
5	1.598	0.106	-0.060	0.104	0.212	1.827	0.144	0.227	0.223	0.202
		(0.93)	(-0.56)	(1.02)	(2.20)			(1.17)	(1.19)	(1.05)
6	1.531	0.038	-0.071	0.202	0.275	1.679	-0.005	-0.046	-0.058	-0.094
		(0.31)	(-0.55)	(1.91)	(2.59)			(-0.28)	(-0.34)	(-0.54)
7	1.648	0.155	0.018	0.263	0.350	1.977	0.294	0.127	0.069	0.050
		(-1.27)	(0.13)	(2.21)	(2.95)			(0.61)	(0.38)	(0.27)
8	1.322	-0.171	-0.242	0.077	0.163	2.208	0.525	0.361	0.284	0.297
		(-1.27)	(-1.71)	(0.67)	(1.41)			(1.52)	(1.73)	(1.75)
9	1.225	-0.267	-0.322	-0.054	0.071	2.071	0.388	0.214	0.133	0.148
		(-1.79)	(-2.03)	(-0.36)	(0.48)			(0.80)	(0.63)	(0.68)
Hi	1.373	-0.119	-0.181	0.037	0.188	1.677	-0.007	-0.268	-0.343	-0.356
		(-0.85)	(-1.21)	(0.25)	(1.38)			(-0.83)	(-1.14)	(-1.15)
Lo – Hi	0.267	0.267	0.342	-0.015	-0.211	-0.644	-0.644	-0.065	0.052	0.118
		(1.37)	(1.65)	(-0.08)	(-1.14)		(-1.02)	(-0.12)	(0.11)	(0.24)
2 - 9	0.331	0.331	0.395	0.069	-0.065	-0.437	-0.437	0.029	0.119	0.194
		(1.68)	(1.89)	(0.35)	(-0.32)		(-0.75)	(0.05)	(0.33)	(0.52)

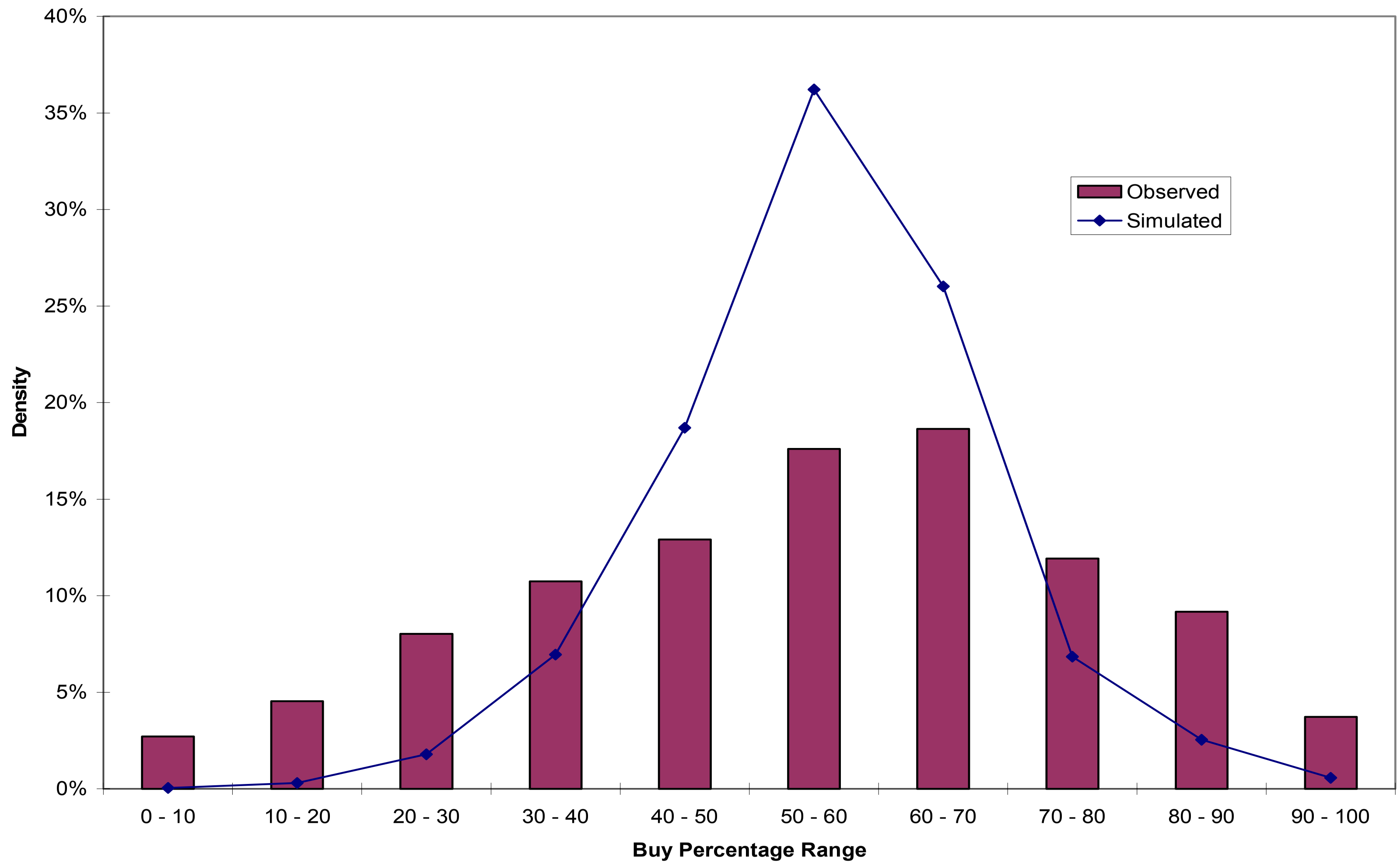

Figure 1a: Observed and Simulated Distribution of Percentage Buys for Large Discount Broker, 1991-1996

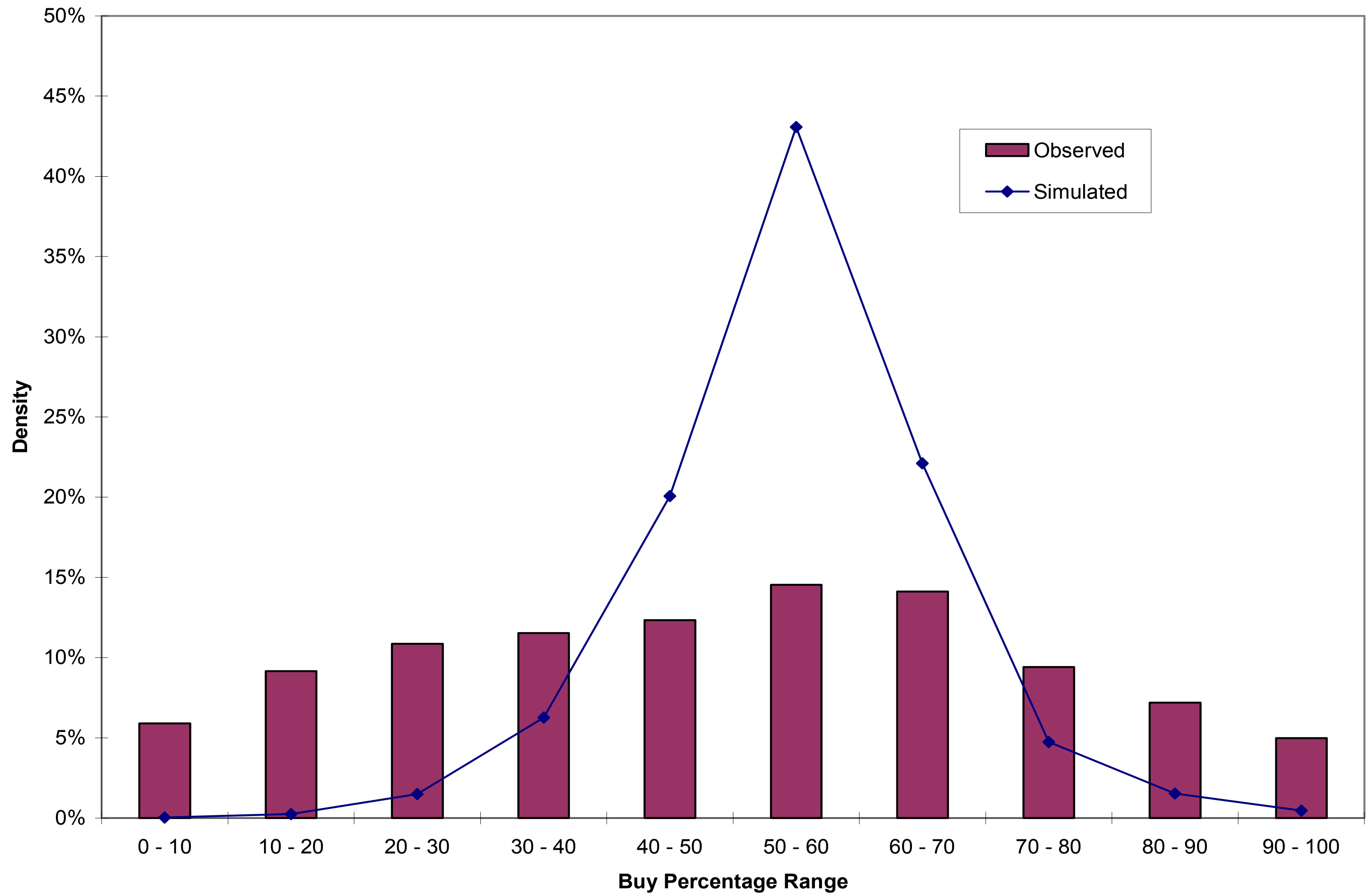

Figure 1b: Observed and Simulated Distribution of Percentage Buys for Large Retail Broker, 1997-1999

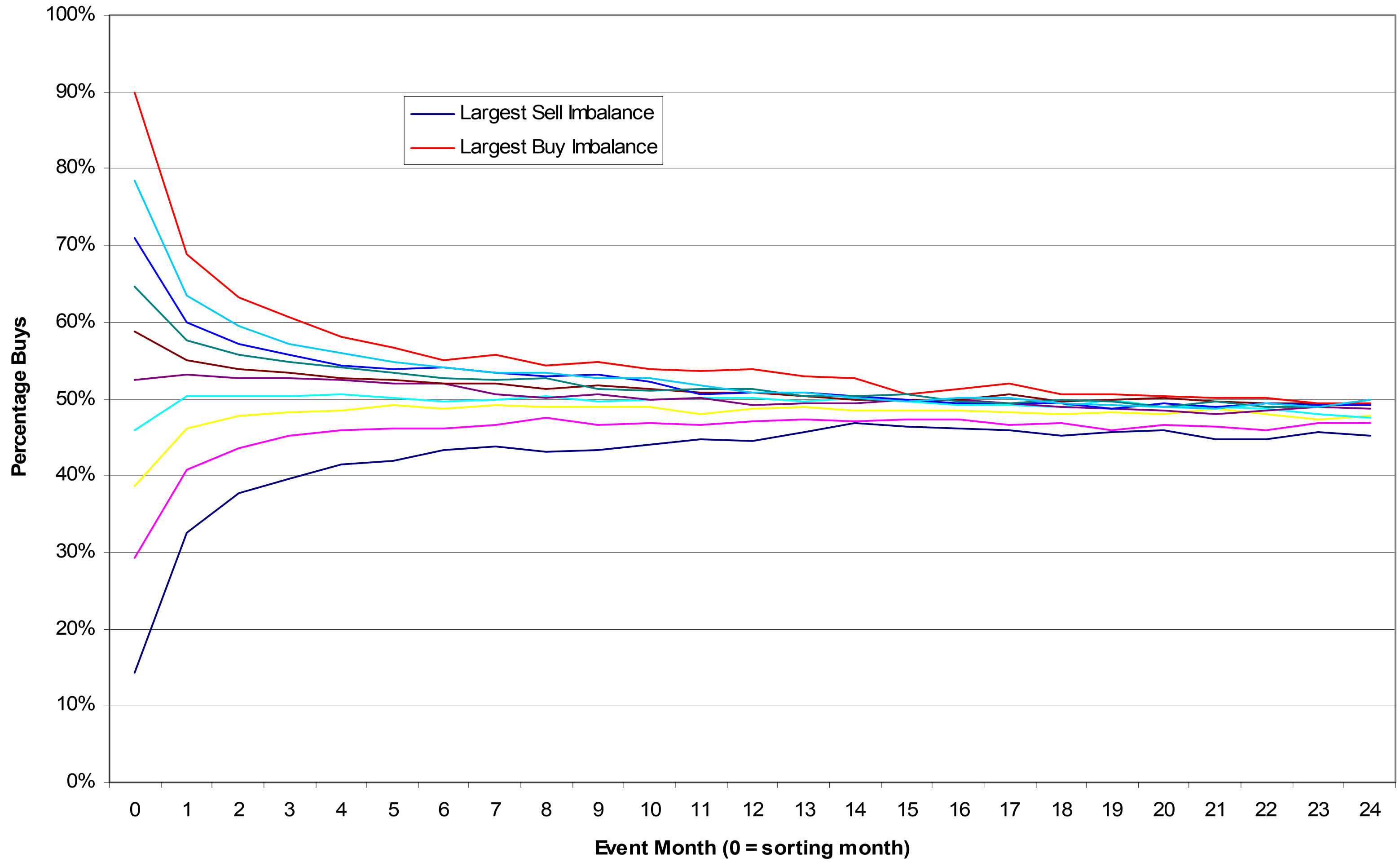

Figure 2a: Percentage Buys in Event Time for Large Discount Broker, 1991-1996.

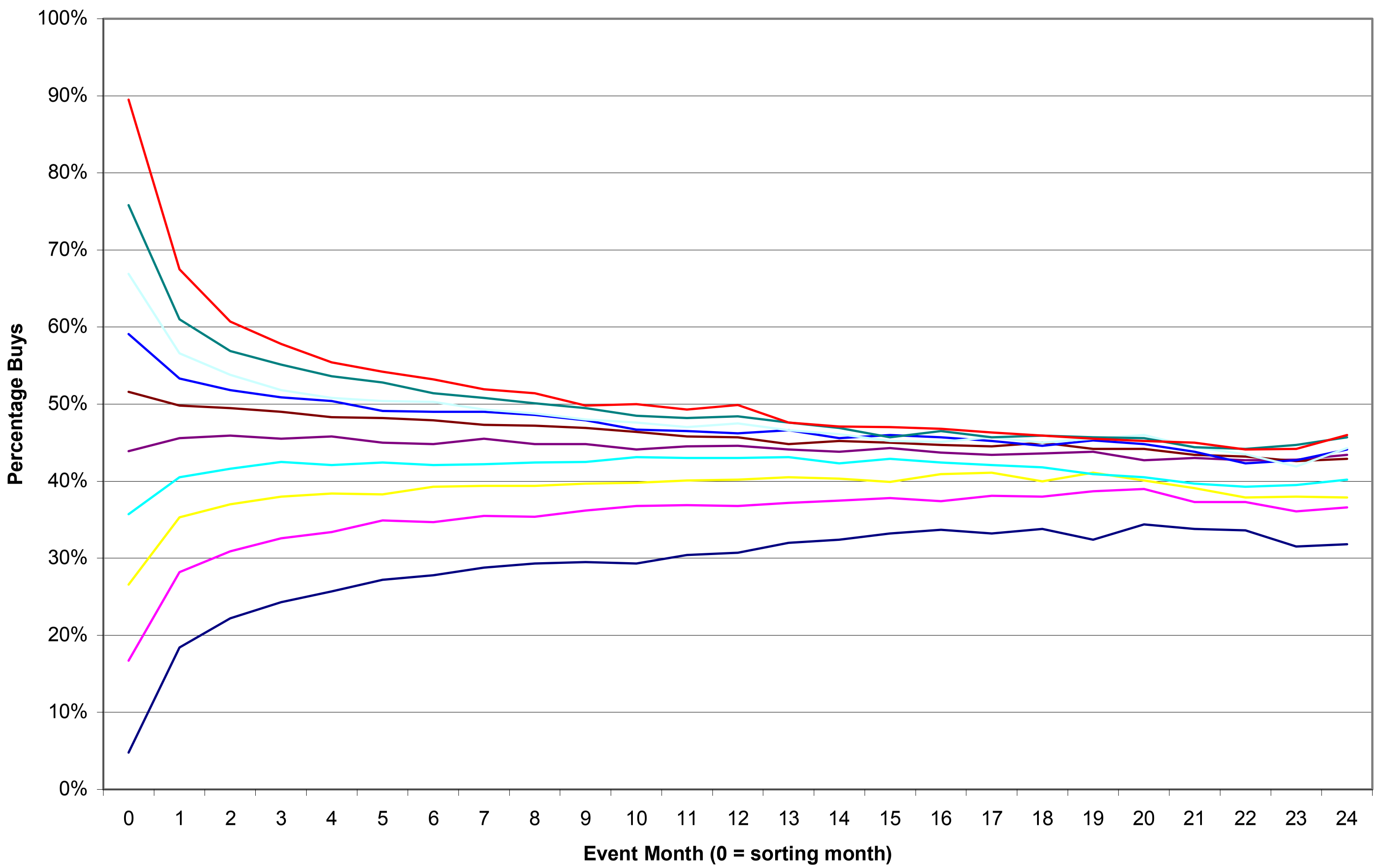

Figure 2b. Percentage Buys in Event Time for Retail Broker, 1997-1999.

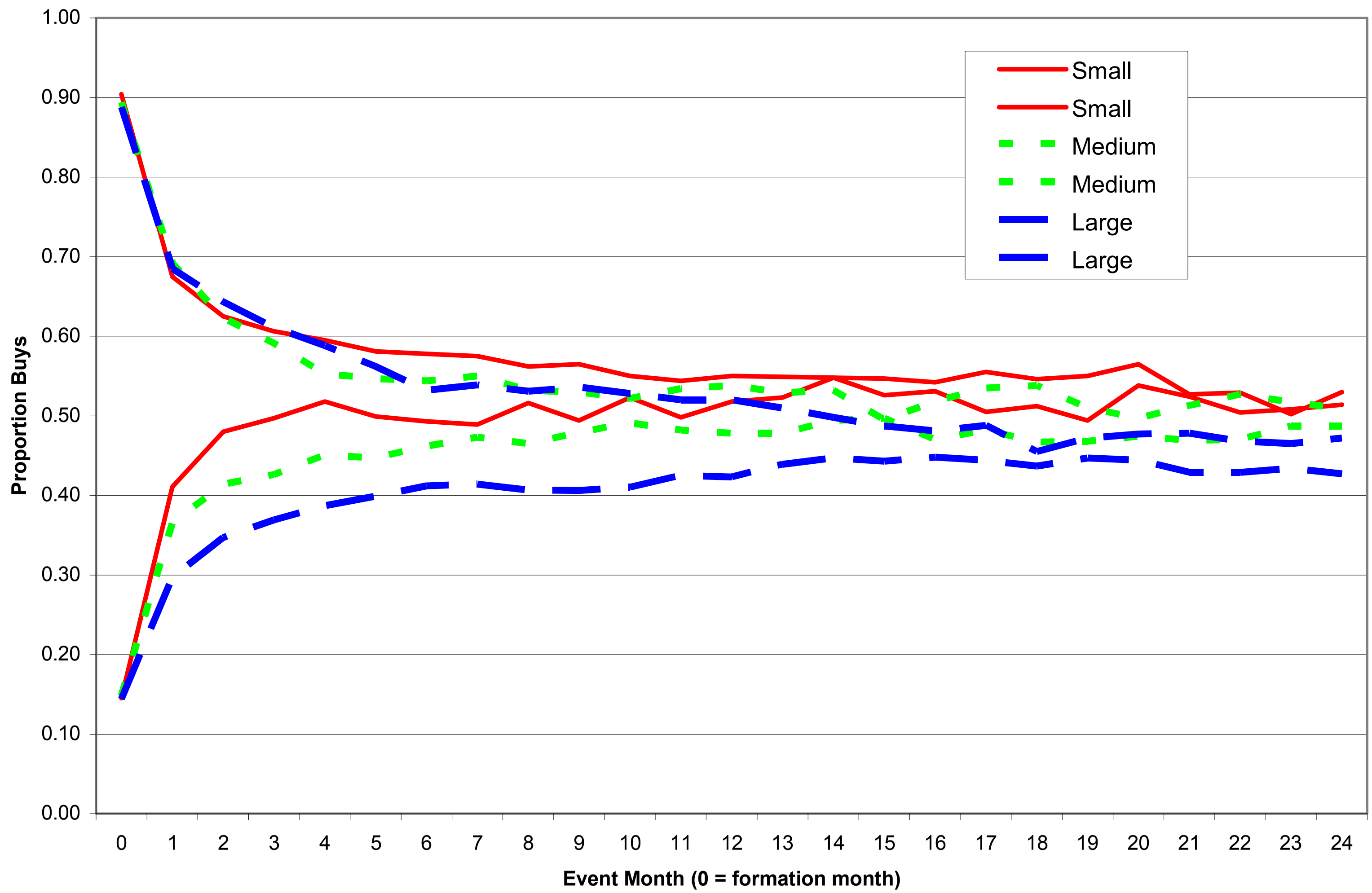

Figure 3a: Percentage Buys in Event Time by Firm Size for Large Discount Broker, 1991-1996

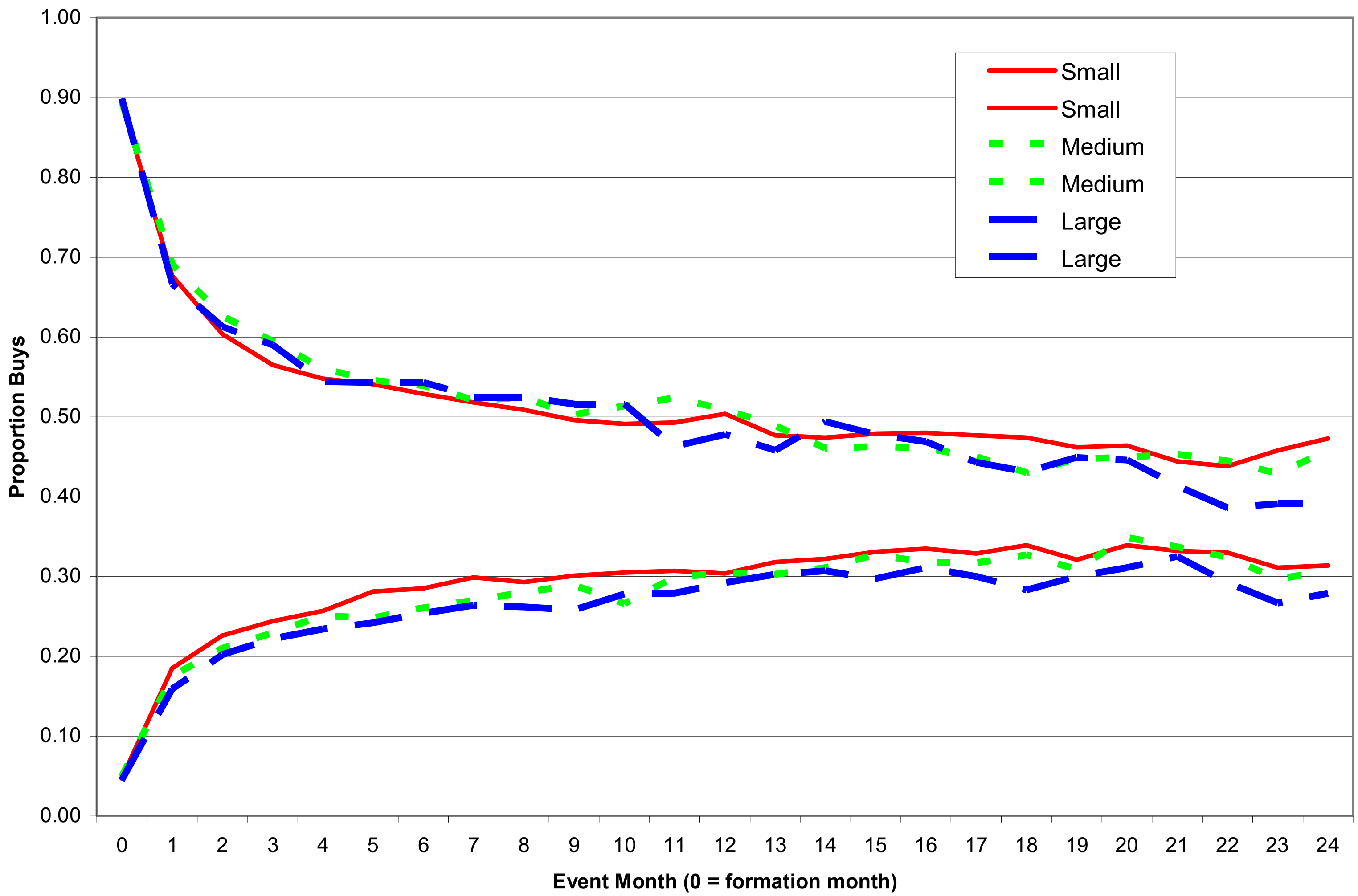

Figure 3b: Percentage Buys in Event Time by Firm Size for Large Retail Broker, 1997-1999

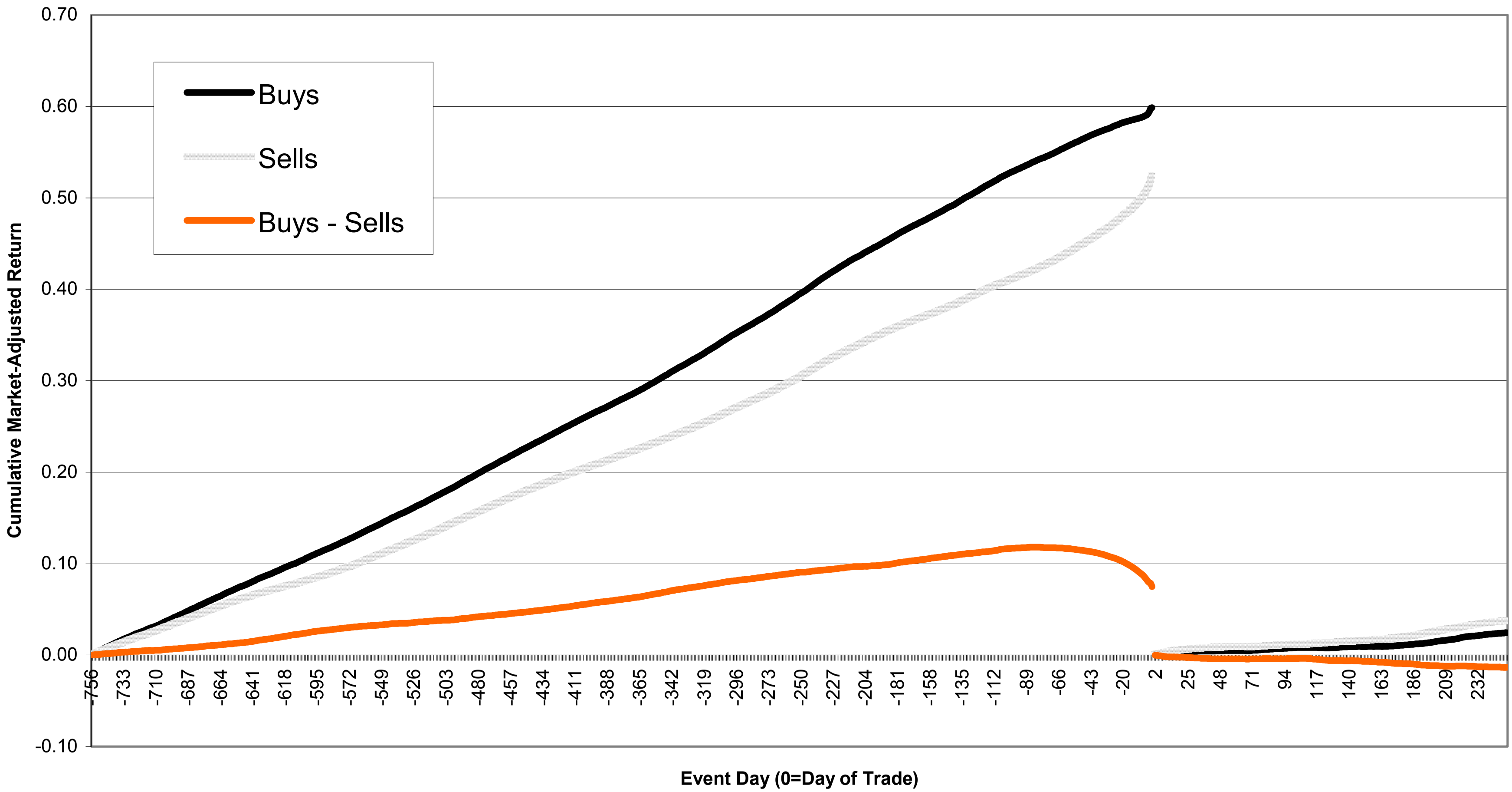

Figure 4a: Cumulative Market-Adjusted Returns around Purchases and Sales in Event Time for Large Discount Broker, 1991-1996.

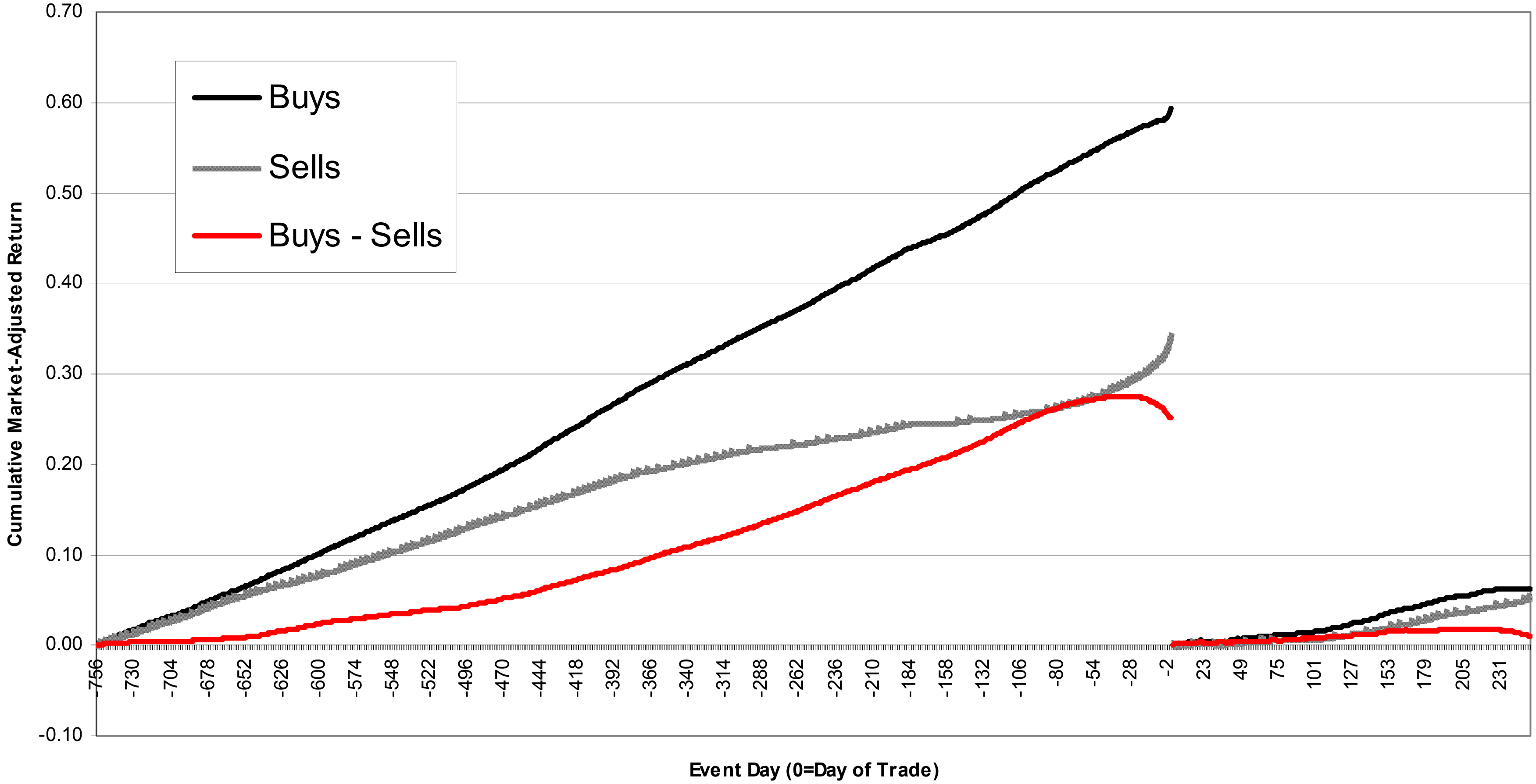

Figure 4b: Cumulative Market-Adjusted Returns around Purchases and Sales in Event Time for Large Retail Broker, 1997-1999.