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Systematic noise

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Abstract

We analyze trading records for 66,465 households at a large discount broker and 665,533 investors at a large retail broker to document that the trading of individuals is highly correlated and persistent. This systematic trading of individual investors is not primarily driven by passive reactions to institutional herding, by systematic changes in risk-aversion, or by taxes. Psychological biases likely contribute to the correlated trading of individuals. These biases lead investors to systematically buy stocks with strong recent performance, to refrain from selling stocks held for a loss, and to be net buyers of stocks with unusually high trading volume.

JEL classifications: G11; G14

Keywords: Individual investors; Market efficiency; Herding

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, pp. 529–530). Many theoretical models (e.g., Kyle, 1985) attribute noise traders with

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random aggregate demand and no persistent or predictable influence on stock prices. Black, though, thought that the influence of noise traders would be cumulative.

Although Black did not specify which traders are noise traders, individual investors are prime candidates for the role. According to Black (1986, p. 531), "[m]ost of the time, the noise traders as a group will lose money trading." Though individual investors earn positive returns in rising markets, they lose money trading (Odean, 1999; Barber and Odean, 2000; Barber et al., 2009a, b); 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).

As Shleifer (2000, p. 12) notes, "investor sentiment reflects the common judgment errors made by a substantial number of investors, rather than uncorrelated random mistakes." For changes in investor sentiment to have a significant impact on returns, individual investors must choose to buy the same stocks or sell the same stocks at about the same time; that is, their buy/sell decisions must be correlated. While a substantial literature in institutional herding examines reasons for and evidence of correlated trading across institutional investors,[3] 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 et al., 1992; Welch, 1992), or a common rational response to correlated information. In Section 4, we argue that these mechanisms are unlikely to coordinate the trading of individual 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; Shapira and Venezia, 2001; Dhar and Zhu, 2006). They also sell stocks with recent gains (Odean, 1999; Grinblatt and Keloharju, 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 et al., 2004). Investors tend to buy stocks that catch their attention (Barber and Odean, 2008). And investors tend to underdiversify in their stock portfolios (Lewellen et al., 1974; Barber and Odean, 2000; Goetzmann and Kumar, 2008); and in their retirement accounts (Benartzi and Thaler, 2001; Benartzi, 2001).[4]

For changes in investor sentiment to have a significant cumulative effect on asset returns, 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

[3]For example, Lakonishok et al. (1992), Grinblatt et al. (1995), Wermers (1999), and Sias (2004).

[4]Other related work includes Kumar (2007), 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 et al. (2003), who develop a measure of investor sentiment using daily mutual fund flow data.

trading. Second, the aggregate trading of individual investors must be systematic (Shleifer, 2000).[5]

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 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 (DeLong et al., 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 investor sentiment to significantly 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 different empirical methods, we find 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% for the discount customers and 75% 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% and that of Australian full-service brokers is 15.9%. Dorn et al. (2008) document cross-sectionally correlated trading in a sample of 37,000 clients of a German discount brokerage from February 1998 through May 2000. Using the large discount brokerage data analyzed in this paper, Kumar (2007) finds that individual investors systematically shift their preferences across extreme style portfolios, such as value versus growth.

[5]Widespread biases that affect the demand for some assets will influence equilibrium asset prices even if the biases of investors are independent (see Bossaerts et al., 2007). Our point is that changes in individual beliefs due to biased decision making must be correlated if those changes are to appreciably affect asset returns. Of course, the trades of even the smallest investor may have some incremental affect on prices, especially for illiquid assets.

Kumar and Lee (2006) report that investors at a US discount brokerage are also systematic in their movements of money in and out of equity markets. Kumar and Lee attribute correlated movements in and out of the market to changes in investor sentiment. Kaniel et al. (2008) also examine the question of whether the trades of individual investors are systematic in the sense that they affect all stocks at the same time; Kaniel et al. report that they "cannot find strong evidence of a common component in the imbalances of individual investors across stocks." While Kumar and Lee (2006) and Kaniel et al. (2008) examine the tendency of individual investors to 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.

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.

Naturally, these results raise the following question: What are the primary factors that coordinate the trades of individual investors? To answer this question, we consider factors that others have suggested may coordinate the trades of institutional investors, including taxes and psychological biases. We present evidence suggesting that the primary factors that coordinate the purchase decisions of individual investors are the overextrapolation of past returns—one manifestation of the Tversky and Kahnemann (1974) representativeness heuristic, the disposition effect, and limited attention.

In the next section, we describe the data and our empirical methods for analyzing correlated trading by individual investors. We present results of this analysis in Section 2. In Section 3, we consider what factors may be responsible for coordinating the trading of individual investors. Section 4 concludes.

1. Data and methods

1.1. 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.

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)

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.

1.2. Distribution analysis

We employ three approaches to test whether the decisions to purchase versus sell are correlated across individual investors. We employ the standard measure of herding first used by Lakonishok et al. (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, given the overall observed level of buying ($E[p_{it}]$), the decisions of different individual investors to buy versus sell specific stocks are uncorrelated. Specifically, the herding measure for stock i in month t is calculated as

$$HM_{it} = |p_{it} - E[p_{it}]| - E|p_{it} - E[p_{it}]|. \qquad (1)$$

The latter term in this measure—$E|p_{it} - E[p_{it}]|$—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% 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% buys out of ten trades. This analysis is done across all stocks and all months to create a simulated distribution of p_{it}.

1.3. Correlation analysis

1.3.1. Contemporaneous correlation

Our second approach to test correlated buy/sell decisions is straightforward—we calculate the correlation in the buy/sell decisions of randomly assigned groups. If buy/sell decisions are uncorrelated 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 randomly chosen 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.[6] 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.

We test the null hypothesis that buying intensity across stocks is uncorrelated across individual investors. This is analogous to the standard null hypothesis in the institutional herding literature. Zero correlation is clearly the appropriate null if one's objective is to show that the trading of individual investors is correlated. However, non-zero correlated trading by individual investors does not in and of itself prove that investors are trading for psychological reasons. Pecuniary considerations, such as taxes, could lead to some degree of correlated trading by individual investors. In Section 3, we present evidence that factors such as taxes are not the principal determinants of correlated trading by individuals.[7]

1.3.2. 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

[6] 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.

[7] Furthermore, if a reader believes that such rational considerations should lead to a particular level of correlated trading, one can easily use the standard errors implied by the t-statistics reported in Table 3 (discussed below), to test whether that level of correlated trading is consistent with our empirical findings.

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 null hypotheses for each lag length (L) at each brokerage: That the correlation of buying intensity in month t and month $t+L$ is 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 $t+L$.

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 $L = 1,\ldots,24$.

2. Results

2.1. Distribution results

In Fig. 1, we present the observed and simulated distributions 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. The line represents the distribution simulated under the assumption that the probability of any transaction being a purchase is equal to the ratio of all purchases divided by all trades in the database. 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 the contemporaneous buy/sell decisions of individual investors are uncorrelated.

2.2. 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 of Table 2 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%) in buying intensity. In a given month, both groups tend to concentrate their buying in the same stocks.[8]

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.

[8] In Table 3, Panel A presents the means of percentage buys correlations estimated each month during our sample period for two randomly chosen groups of 31,382 households at the large discount brokerage firm. As a robustness check, we re-calculate the (contemporaneous) mean percentage buys correlation for 1,000 different pairs of random groups of 31,382 households. The minimum contemporaneous mean monthly percentage buys correlation is 71.5% and the maximum 73.9%. We also estimate correlations for 1,000 randomly selected pairs of groups of 10,000 investors each. The average contemporaneous mean monthly percentage buys correlation is 68.3%. On average, correlations drop as the number of investors in each group drops because, when fewer trades are observed, the strength of the common component of trading relative to the idiosyncratic component is smaller.

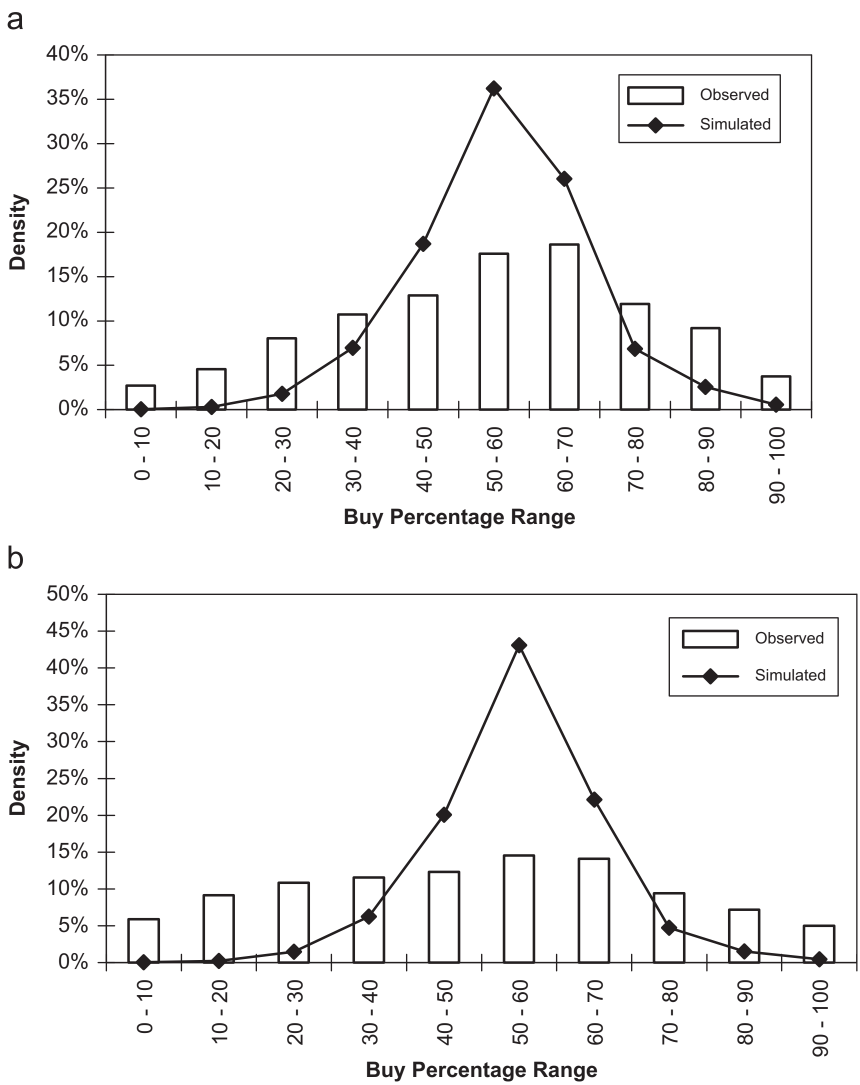

Fig. 1. Observed and simulated distribution of percentage buys. For each stock in each month for which we observe at least ten trades, we calculate the percentage of trades in our database that are purchases. We plot a histogram of the observed distribution across all stock-months. We then simulate the expected distribution under the assumption that the probability of any transaction being a purchase is equal to the ratio of all purchases divided by all trades in the database. (a) Large discount broker, 1991 to 1996. (b) Large retail broker, 1997–1999.

The remaining rows of each panel present the time-series correlations between buying activity in month t and month $t+L$, where $L = 1,\ldots,24$. For example, the correlation between buying intensity in month t and month $t+1$ ranges from 46.7% to 48.2% for the two groups at the large discount broker and from 55.8% to 58.6% 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

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, is the proportions of all stock traded by sample individual investors during month t that are purchases, and 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 ten 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% are classified as large firms, the bottom 30% as small, and the remaining firms as medium. (p-values are in parentheses.)

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

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.

Figs. 2a and b 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 (Fig. 2a). For stocks with the greatest buying intensity, on average 90% of trades are buys in the formation month; for stocks with the least buying intensity, on average 14% 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% buys for the top decile and 33% buys for the bottom decile). The spread dissipates slowly over time to 9% after 12 months and 4% after 24 months.

The results for the large retail broker (Fig. 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% buys for the top decile and 17% 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.

3. The determinants of correlated trading by individual investors

A wide variety of factors could potentially coordinate the trading of individual investors. Individual investor trading could be correlated for the same reasons that have been proposed to explain institutional herding, including principal-agent concerns, informational cascades, and correlated information. Correlated trading could result from individual investor limit orders systematically executing against market orders of institutions who herd, from common responses to tax law (e.g., late in the year tax-loss

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 (1/91–11/96) and a large retail broker (1/97–6/99). 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 month 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* (1/91–11/96)

Horizon (L)	Correlation of % buys in month t with % buys in month $t+L$			t-Statistics		
	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* (1/97–6/99)

Horizon (i)	Correlation of % buys in month t with % buys in month $t+i$			t-Statistics		
	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*

Table 3 (*continued*)

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 1% and 5% level, respectively.

selling), or from systematic changes in individual investors' risk-aversion. Finally, shared psychological factors, such as the representativeness heuristic, the desire to postpone regret, and limited attention could coordinate the trading of individuals.

3.1. Principal-agent concerns, informational cascades, and correlated information

A large number of papers discuss the causes of and test for evidence of institutional herding. Proposed determinants of institutional herding include principal-agent concerns, rational information cascades, and rational responses to correlated information. The correlated trading of individual investors is, most likely, not driven by these same mechanisms.

One example of how principal-agent concerns could coordinate institutional trading is that 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). Such principal-agent concerns will not apply to individual investors trading on their own account at a discount brokerage. Since we document strongly correlated trading among such investors, we do not believe that principal agent concerns are a major determinant of correlated trading by individual investors.

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 the individual investors studied here.[9] First, most individual investors—though they can observe aggregate trading—do not have reliable information about which

[9]Feng and Seasholes (2004) 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.

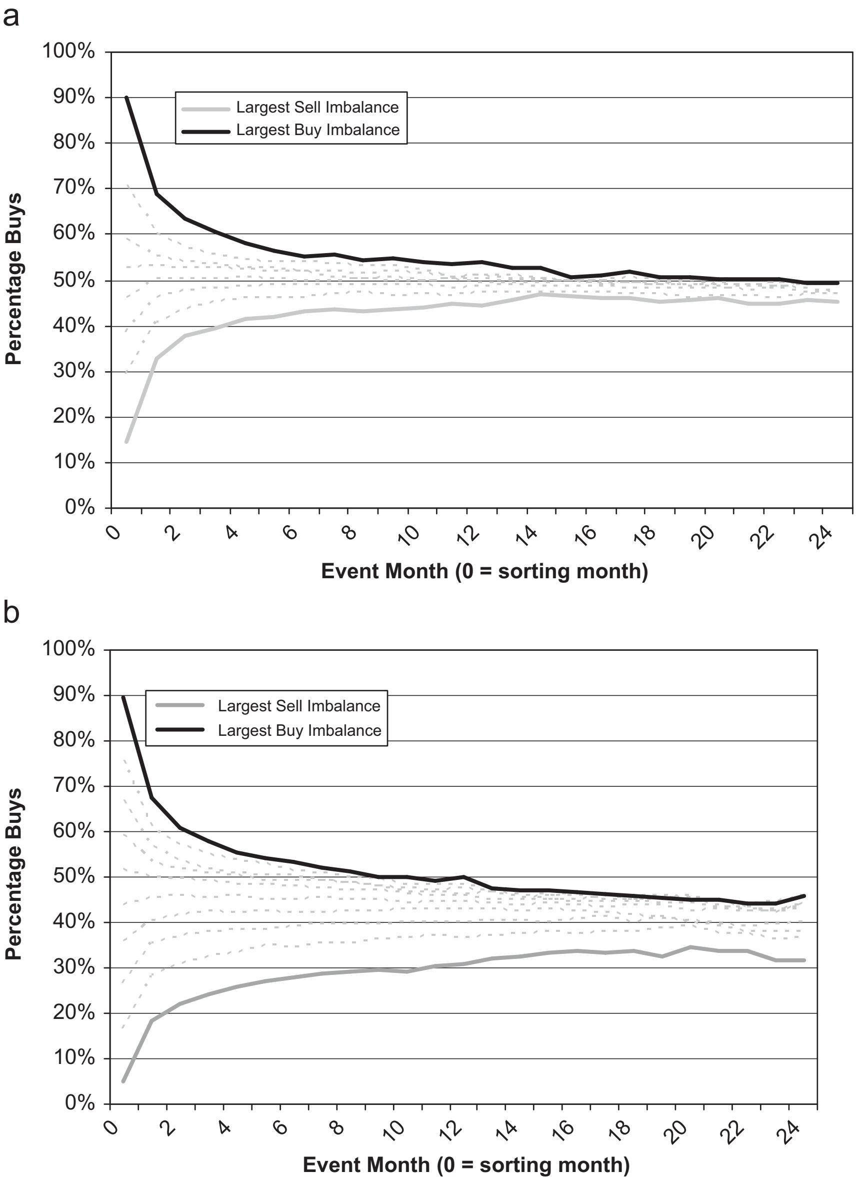

Fig. 2. Percentage buys in event time. Each month we sort stocks into ten deciles based on percentage of trades that are buys in the brokerage data holding the decile composition constant, we then calculate the percentage buys in each of the 24 subsequent event-time months. The graphs represent the means of our event-time analyses. (a) Large discount broker, 1991–1996. (b) Large retail broker, 1997–1999.

trades were executed by other individuals. Second, on average, the trades of individual investors are wealth reducing not wealth enhancing (Odean, 1999; Barber and Odean, 2000; Barber et al., 2009a, b). 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 mean monthly contemporaneous percentage buys correlation is very similar for both discount (73.4%) and retail investors (75.1%). Furthermore, broker advice cannot explain the long persistence in auto-correlated buying intensity, unless brokers are remarkably unwavering in their specific recommendations.

A large number of empirical papers test for institutional herding. Many report little evidence of herding. Lakonishok et al. (1992) analyze the holdings of pension funds for the five years ending in 1989 and conclude "pension funds herd relatively little." Grinblatt et al. (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 1975–1999 period and concludes there is "little herding by mutual funds in the average stock." Sias (2004) 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.

3.2. *Passive responses of individual investors to institutional herding*

One possibility is that the contemporaneous correlation in the buying and selling of individual investors is the result of their reacting passively, via unmonitored limit orders, to herding of institutional investors. To best test this requires data on market versus limit orders. Unfortunately, the trade data we use do not distinguish limit orders 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 elimination of these trades is likely to exclude the bulk of executed limit orders. In both datasets, this filter rule eliminates roughly half of all trades. Using the filtered trade data, we recalculate our main results.[10] 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%—virtually identical to the 73.4% reported in Table 3, Panel A 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%—also very similar to the 75.1% reported in Table 3, Panel B 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 document represents the active decisions of individual investors.

Further evidence that our results are not driven by limit orders comes from Barber et al. (2009b), who use the NYSE Trades and Quotes (TAQ) database to show that the buying

[10]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.

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[11] that they use to sign trades as buyer or seller initiated are specifically designed to identify active, not passive (e.g., limit order), trades. Dorn et al. (2008) document correlated trading in market orders at a German discount brokerage.

3.3. Taxes

Tax considerations could potentially coordinate individual investor trading through mechanisms such as end of the year tax-loss selling. To evaluate the importance of taxes as a coordinating factor, we estimate correlated trading separately for taxable accounts and tax-deferred accounts (e.g., IRAs) at the two brokerage firms. We merge all taxable accounts at each household and all tax-deferred accounts. We form two randomly selected groups of 14,000 (120,000) taxable accounts and two randomly selected groups of 14,000 (120,000) tax-deferred accounts at the large discount broker (large retail broker). We then calculate the mean monthly contemporaneous percentage buys correlation (as described in Section 1.3.1) between the taxable groups and between the tax-deferred groups. For the taxable accounts, the mean monthly contemporaneous percentage buys correlation is 46.0% at the discount broker and 61.6% at the retail broker; for the tax-deferred accounts it is 53.1% at the discount broker and 74.7% at the retail broker.[12] Since the correlation of trades is higher in tax-deferred accounts, taxes do not appear to be a major determinant of correlated trading.

3.4. Common shifts in risk-aversion

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.

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.

[11]See Lee and Ready (1991) and Ellis et al. (2000).

[12]As discussed in footnote 6, percentage buys correlations are smaller when one observes smaller samples. These tax-related analyses reduce sample size by reducing group sizes to 14,000 households at the large discount brokerage and 120,000 at the large retail brokerage (approximately the maximum number of equal size groups we are able to form that meet our minimum trading requirements) and by looking at only the taxable trades or the tax-deferred trades for each household rather than pooling these trades.

We use NYSE breakpoints to determine firm size; the bottom 30% are classified as small firms, the middle 40% as medium, and the top 30% as large. Firms listed on the 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 do not observe a dramatic reduction in the herding measures for stocks of similar size. Thus, our evidence does not support the hypothesis that shifts in risk preferences are a major determinant of cross-sectionally correlated trading by individual investors.[13]

3.5. *Psychological biases*

Common decision biases may serve to coordinate the trading of individual investors. We examine how three previously documented behaviors, attributable to decision biases, contribute to correlated trading by individual investors. These behaviors are the tendency to chase performance, the tendency to more readily sell stocks held for a profit than those held for a loss (i.e., the disposition effect), and the tendency to be net buyers of stocks with unusually high trading volume.

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). DeBondt and Thaler (1985, 1987) argue the representativeness heuristic causes investors to overweight the importance of past returns when forecasting future returns. If the representativeness heuristic is the primary force that coordinates individual investor trades, we would expect purchases to be concentrated in stocks with strong past returns and sales to be concentrated in stocks with poor past returns.

Previous studies have documented that individual investors tend to hold onto losing investments and sell winners.[14] 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. Thus the disposition effect and the representativeness heuristic, lead to opposite predictions about which stocks investors tend to sell.

Barber and Odean (2008) 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 *limited attention* and are generally not able to easily rank hundreds, much less thousands, of choices. Investors may manage the problem of choosing among thousands of possible stock purchases by limiting their search to stocks that have recently caught their attention.

[13]Kumar (2007) documents individual investor preferences for small versus large and value versus growth stocks change over time. Our results indicate this is not the primary factor coordinating trade across stocks.

[14]See Odean (1998)—common stocks, Genesove and Mayer (2001)—real estate (Heath et al., 1999)—company stock options, and Locke and Mann (2005)—futures.

Attention is less of an issue for selling because most individual investors hold relatively few individual common stocks in their portfolio (Barber and Odean, 2000; Goetzmann and Kumar, 2008) and most individual investors do not sell short. Barber and Odean (2008) propose that high abnormal trading volume is one indication that investors are paying attention to a stock. If attention is an important determinant of correlated trading by individual investors, we would expect individual investors to be net buyers of stocks with high abnormal trading volume.

To see how, or if, investors react to past returns, we first 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 Fig. 3, 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, though not by such a large margin over the three prior years. Over the three or four months prior to the transaction, stocks sold tend to outperform stocks purchased. This buying behavior is consistent with the representativeness heuristic though the selling behavior is not. Selling behavior is consistent with the disposition effect.

We augment our graphical analysis by estimating the following cross-sectional regression:

$$PB_{it} = a_t + \sum_{j=1}^{12} b_{jt} R_{t-j} + c_t AV_{it} + d_t PB_{i,t-1} + \varepsilon_{it}, \tag{2}$$

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, where abnormal trading volume is calculated as a stock's trading volume in month 0 divided by it's average trading volume over the previous twelve months, 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 squares 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:

$$\frac{B_{it}}{P_{it}} = a_t^b + \sum_{j=1}^{12} b_{jt}^b R_{t-j} + c_t^b \frac{B_{i,t-1}}{P_{i,t-1}} + \varepsilon_{it}^b, \tag{3a}$$

$$\frac{S_{it}}{P_{it}} = a_t^s + \sum_{j=1}^{12} b_{jt}^s R_{t-j} + c_t^s \frac{S_{i,t-1}}{P_{i,t-1}} + \varepsilon_{it}^s, \tag{3b}$$

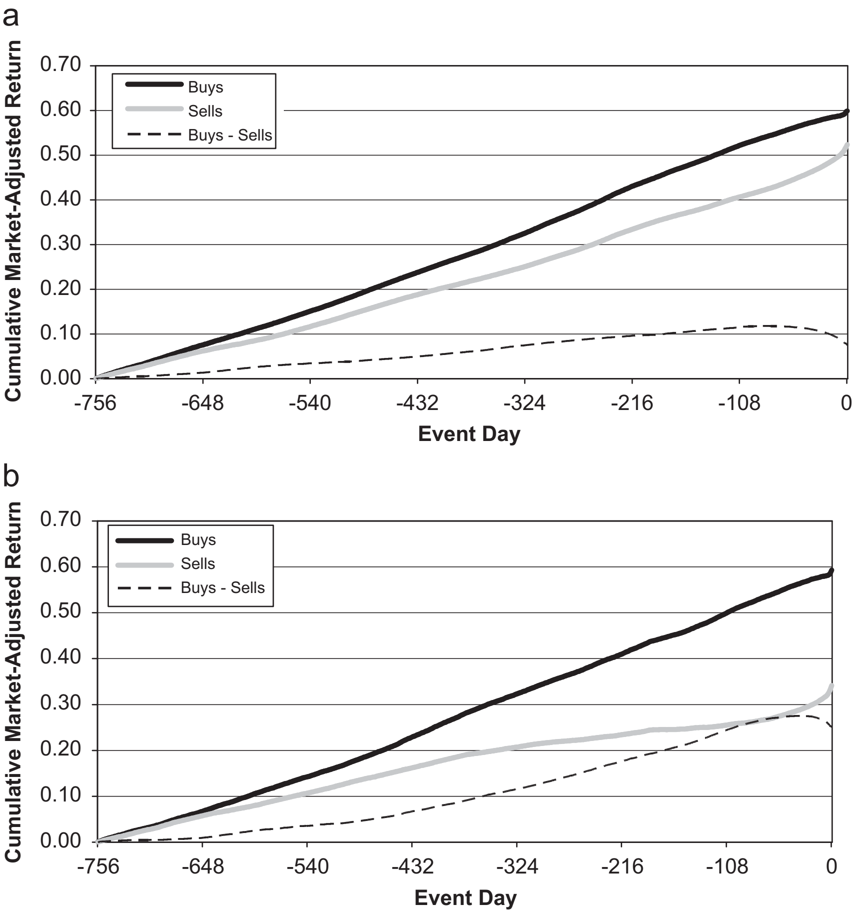

Fig. 3. Cumulative market-adjusted returns around purchases and sales in event time. We calculate the mean market-adjusted return on all purchases in event time, where day 0 is the day of the purchase. These means are cumulated beginning three years (756 trading days) prior to the purchase. There is an analogous calculation for sales. For each brokerage, we plot the cumulative mean market-adjusted return for buys and sells. (a) Large discount broker, 1991–1996. (b) Large retail broker, 1997–1999.

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 to June 1999).

Table 4
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)*

The results of this analysis are presented in Table 4. 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.

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 weak in the quarter before the transaction, peaks in quarter $t-4$, and dissipates slowly in earlier quarters. Individual investors also sell stocks with strong past returns. Right before a sale, the relation is strong; in prior quarters it 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. Buying behavior, but not selling behavior, is consistent with the representativeness heuristic; selling behavior is consistent with the disposition effect.

To better understand the importance of the disposition effect as a determinant of correlated trading, we partition investors at the large discount brokerage firm on their tendency to display the disposition effect during the first three years of our sample (1991–1993). We then estimate the subsequent (1994–1996) cross-sectional correlation of trading for these partitions.

We reconstruct household portfolios at the large discount brokerage from trading records.[15] For the period 1991–1993 and for the period 1994–1996, for each household, we count the number of sales for a gain, sales for a loss, opportunities to sell for a gain, and opportunities to sell of a loss, where gains and losses are relative to purchase price. Opportunities to sell for a gain are actual sales for a gain and stocks held for a gain, but not sold, on a day that an investor sold one or more stocks; opportunities to sell for a loss are actual sales for a loss and stocks held for a loss, but not sold, on a day that an investor sold one or more other stocks (see Odean, 1998 for details). For each household, we then calculate the proportion of gains realized (PGR) as the ratio of sales for a gain to opportunities to sell for a gain and the proportion of losses realized (PLR) as the ratio of sales for a loss to opportunities to sell for a loss. Finally, for each household, we calculate the ratio PGR/PLR for each of our two periods. Households with greater PGR/PLR display a greater disposition effect.[16] To test for persistence in the disposition effect, for each period we rank each household on PGR/PLR and calculate the Spearman rank

[15]We do not perform this analysis for the large retail brokerage investors because the time period of the data is too short.

[16]One can alternatively estimate the disposition effect for each household as PGR–PLR. For our purposes, this alternative specification has the disadvantage that it is also affected by portfolio size. Thus, the correlation of household PGR–PLR from one period to the next could be driven, in part, by persistence in portfolio size. While the measure PGR/PLR does not have the same sensitivity to portfolio size, it is undefined for investors who sold at least one stock for a gain during the sample period but sold no stocks for a loss. For the purposes of these analyses, we classify such investors as having the highest PGR/PLR ranking and belonging to the highest PGR/PLR partition. Our results are qualitatively similar if we use PGR–PLR as a measure of the disposition effect.

correlation between the two periods to be 17.7% ($p < 0.0001$). Thus we can reject the null hypothesis that the tendency of a household to display the disposition effect is not persistent. To test whether households with a greater disposition effect tend to be more correlated in their trading behavior, we create three partitions based on 1991–1993 PGR/PLR: PGR/PLR < 1.0; 1.0 ⩽ PGR/PLR ⩽ 2.33; and 2.33 < PGR/PLR. From households in each partition, we form two randomly selected groups of 2,500 households and calculate the mean monthly cross-sectional correlation between groups of the percentage of trades that are buys.

For the households with no disposition effect in 1991–1993 (i.e., PGR/PLR < 1.0), the mean monthly cross-sectional correlation between the two groups of the percentage of 1994–1996 trades that are buys is 33.5% (t-statistic of 7.12); for the moderate disposition effect households (i.e., 1.0 ⩽ PGR/PLR ⩽ 2.33) the correlation is 38.4% (t-statistic of 9.19), and for the high disposition effect households (i.e., 2.33 < PGR/PLR), the correlation is 54.0% (t-statistic of 14.8). Households that display a greater disposition effect in the first period are much more highly correlated in the second period trading. This is consistent with the hypothesis that this disposition effect is a major determinant of correlated trading by individual investors. However, it is also possible that investors who display more disposition effect share other behaviors that correlate their trading.

The third psychologically motivated investor behavior we examine is the tendency to buy attention-grabbing stocks. We begin with the observation that unusually high trading volume is one indicator that investors are paying unusual attention to a stock. In the cross-sectional analysis reported in Table 4, we see that both the percentage of transactions that are purchases and the number of purchases minus the number of sales divided by the number of positions ($(B_{it}-S_{it})/P_{it}$) are increasing in abnormal trading volume. Thus individual investors are more likely to be on the buy side of the market for attention-grabbing stocks. A simple univariate analysis also 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 5. 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 divided by outstanding shares. Again, share turnover is quite high for all deciles—ranging from 8% to 17% monthly turnover. However, for both datasets, share turnover is greatest in those stocks that are heavily purchased.

We find that individual investor buying and selling decisions are highly correlated with past returns and with contemporaneous trading volume. Investors tend to buy and sell stocks with strong past returns. They are net buyers of stocks that have performed well during the previous one to three years, but net sellers of stocks that have performed well during the previous one to three quarters. Buying past winners is consistent with the representativeness heuristic. Selling past winners is consistent with the disposition effect but not the representativeness heuristic. Odean (1999) suggests that most investors look to the future when deciding which stocks to purchase, but look to the past when deciding what to sell. Thus the expectation that past winners will continue to outperform drives purchase decisions, but the desire to postpone, or even completely avoid, the regret associated with selling for a loss, drives selling decisions. Purchases are also concentrated in attention-grabbing stocks.

Table 5
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 (0.30)	1.53 (0.06)	7.1	44.8	8.43 (0.22)	1.39 (0.06)
2	29.3	28.8	12.00 (0.38)	1.57 (0.07)	16.6	55.9	8.91 (0.18)	1.33 (0.06)
3	38.6	29.7	12.39 (0.48)	1.56 (0.06)	26.5	61.4	9.94 (0.31)	1.31 (0.08)
4	46.0	32.2	13.16 (0.57)	1.68 (0.09)	35.8	61.9	11.06 (0.29)	1.38 (0.07)
5	52.5	32.8	14.43 (0.71)	1.94 (0.10)	44.0	73.3	12.27 (0.41)	1.46 (0.09)
6	58.8	36.5	14.56 (0.76)	1.98 (0.13)	51.7	78.8	14.99 (0.72)	2.10 (0.36)
7	64.6	37.3	15.34 (0.76)	2.39 (0.32)	59.4	98.6	16.36 (1.08)	2.27 (0.37)
8	71.0	38.8	15.47 (0.80)	2.38 (0.21)	67.2	123.3	17.29 (1.34)	2.12 (0.27)
9	78.4	39.4	16.44 (0.91)	2.40 (0.21)	76.1	154.0	17.02 (0.89)	2.01 (0.26)
Hi	89.9	30.9	17.11 (0.86)	2.71 (0.21)	89.8	132.7	13.94 (0.38)	1.94 (0.19)
Lo–Hi	−75.5	−7.0	−6.34 (0.82)	−1.18 (0.19)	−82.7	−87.9	−5.51 (0.51)	−0.54 (0.14)

Our empirical results support the hypothesis that the representativeness heuristic, the disposition effect, and limited attention are important determinants of correlated trading by individual investors. While we consider many potential determinants of correlated trading, our analysis is not exhaustive. Other psychological biases may contribute to correlated trading and investors may also respond to factors such as corporate earnings and the opinions of investment newsletter analysts (see Kumar, 2007). Finally non-psychological factors such as taxes, though not major determinants of correlated trading, may contribute to it.

4. 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%. 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.

The correlated trading of individual investors is not likely to be driven by factors previously proposed to explain institutional herding, such as principal agent concerns, informational cascades, or rational responses to shared information. Neither limit orders, taxes, nor systematic shifts in risk-aversion explain a large part of this correlated trading. Psychologically motivated trading behavior may account for much of the correlation in individual investor buying and selling. Investors tend to buy stocks with strong past returns, which is consistent with the representativeness heuristic. Investors tend to sell stocks with strong recent past returns, which is consistent with the disposition effect. And investors buy stocks with high abnormal trading volume, which is consistent with the theory that due to limited attention, individual investors are likely to be net buyers of attention-grabbing stocks.

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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