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Mutual Fund Herding and the Impact on Stock Prices

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ABSTRACT

We analyze the trading activity of the mutual fund industry from 1975 through 1994 to determine whether funds "herd" when they trade stocks and to investigate the impact of herding on stock prices. Although we find little herding by mutual funds in the average stock, we find much higher levels in trades of small stocks and in trading by growth-oriented funds. Stocks that herds buy outperform stocks that they sell by 4 percent during the following six months; this return difference is much more pronounced among small stocks. Our results are consistent with mutual fund herding speeding the price-adjustment process.

DO INSTITUTIONAL INVESTORS "FLOCK TOGETHER" (or "herd," as it is often called) when they trade securities? Do some investors follow the lead of others when they trade? Such questions have interested researchers for some time, and are central to understanding the impact of institutional trading on securities markets and to understanding the way in which information becomes incorporated into market prices.[1]

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[1] At the end of 1989, institutional investors held \$1.7 trillion in corporate equities, or 43.5 percent of total equities outstanding in the United States (New York Stock Exchange (1991)), of which mutual funds held \$246 billion (Investment Company Institute (1994)). Institutional trading, when added to member trading, accounted for about 70 percent of total NYSE volume in 1989 (Schwartz and Shapiro (1992)). By June 1997, mutual funds held more than \$2 trillion in equities and \$4 trillion in total assets.

Many newsmedia commentators, including two well-known figures on a recent *ABC Nightline* news program, tend to believe that institutional investors focus excessively on short-term trading strategies, and that they often pile into and out of the same stocks at the same time in a manner that is unwarranted by information about fundamentals.[2] These actions, they argue, increase the volatility of financial markets and force corporations to focus on short-term earnings rather than long-term strategies.[3] Indeed, the large body of research on "fads" in stock market prices is suggestive of large groups of investors with similar styles trading together.

There are four popular theories explaining why institutional investors might trade together. First, managers may disregard their private information and trade with the crowd due to the reputational risk of acting differently from other managers (Scharfstein and Stein (1990)). Second, managers may trade together simply because they receive correlated private information, perhaps from analyzing the same indicators (Froot, Scharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam, and Titman (1994)). Third, managers may infer private information from the prior trades of better-informed managers and trade in the same direction (Bikhchandani, Hirshleifer, and Welch (1992)), and fourth, institutional investors may share an aversion to stocks with certain characteristics, such as stocks with lower liquidity or stocks that are less risky (Falkenstein (1996)).[4]

Some recent empirical evidence is provided by Lakonishok, Shleifer, and Vishny (1992), who find weak evidence of pension fund managers either engaging in positive-feedback trading or trading in herds, with slightly stronger evidence of both in small stocks. Other evidence is provided by Grinblatt, Titman, and Wermers (1995) and Wermers (1997), who document that the majority of mutual funds use positive-feedback trading strategies to select stocks, and that such funds outperform other funds before expenses are deducted. Also, Graham (1999) examines the tendency for analysts who publish investment newsletters to herd. Finally, Sias and Starks (1997) find that institutional investor trading patterns contribute to serial correlation in daily stock returns, and Nofsinger and Sias (1998) compare the trading patterns of institutional and individual investors.

Less recent evidence includes research by Klemkosky (1977), Kraus and Stoll (1972), and Friend, Blume, and Crockett (1970). Klemkosky analyzes stocks having the largest trade imbalances among investment companies

[2] On the *ABC Nightline* program ("What goes up . . .") aired Friday, November 7, 1997, during an interview regarding the role of institutional investors in the stock market, Jason Zweig of *Money Magazine* commented: "Mutual fund managers are extremely focused on the short term." This was followed by Louis Rukeyser of *Wall $treet Week*, who stated: "They (large investors) buy the same stocks at the same time and sell the same stocks at the same time."

[3] Shiller (1991) presents an excellent discussion of this issue.

[4] This aversion could be driven by several factors, including a higher need of funds for liquidity than other investors (resulting in an aversion to small, illiquid stocks) or a fund manager employment contract that encourages risk-taking (resulting in a preference for riskier stocks).

(mainly mutual funds) during each quarter of the period 1963–1972. Large buy imbalances (dollar purchases exceeding dollar sales by the funds) usually follow a prolonged period of positive abnormal stock returns, which is interpreted as evidence that some funds follow other "leader" funds in their purchases.[5]

Kraus and Stoll (1972) study monthly trades for each of 229 mutual funds or bank trusts from January 1968 to September 1969 to determine the tendency of these institutions to herd in their trades. They find dramatic dollar imbalances between purchases and sales in the average stock, but they attribute these imbalances to chance, and not to intentional parallel trading. Finally, a classic study by Friend et al. (1970) finds a significant tendency for groups of mutual funds to follow the prior investment choices of their more successful counterparts (which they call "follow-the-leader behavior") during one quarter in 1968.

In our study, we provide the most comprehensive empirical evidence to date by investigating, over a 20-year period, whether mutual funds herd in their trades. Additionally, we determine whether any such herding impacts stock prices, and whether any such impact is stabilizing or destabilizing. Commonly cited ways in which institutions destabilize stock prices and increase market volatility include herding and positive-feedback trading strategies.[6]

If funds buy stocks in a destabilizing manner (e.g., Scharfstein and Stein (1990)), we should observe a stock price increase followed by a decrease. However, if funds buy stocks in a stabilizing manner (e.g., Hirshleifer et al. (1994)), we should observe a price increase without a subsequent price decrease. To investigate whether herding tends to be stabilizing or destabilizing, we examine long-term return patterns of stocks traded by "herds." To investigate the degree to which herding is related to the use of feedback trading styles, we measure the tendency of funds to herd into (or out of) stocks that are past "winners" versus stocks that are past "losers."

To measure herding by the funds, we begin with the quarterly equity holdings of virtually all mutual funds existing at any time between 1975 and 1994. We apply the measure of herding proposed by Lakonishok et al. (1992), which examines the proportion of funds trading a given stock that are buy-

[5] Large sell imbalances tend to follow a few months of negative abnormal returns that are preceded by a prolonged period of positive abnormal returns. Again, this is attributed to some leader institutions being first in perceiving that the stocks are overvalued after their price run-up.

[6] However, herding and/or positive-feedback trading strategies need not be destabilizing; such trading destabilizes prices if funds buy overpriced and sell underpriced stocks, but stabilizes prices if funds do the opposite. For example, positive-feedback trading could bring stock prices closer to their "true values" if investors underreact to news. See Lakonishok et al. (1992) for an excellent discussion of the stabilization versus destabilization arguments, and Chan, Jegadeesh, and Lakonishok (1996) for evidence that implicates investor underreaction as a likely cause of the high (low) long-term returns of stocks having high (low) price or earnings momentum.

ers. Funds are considered to exhibit herding behavior if stocks tend to have large imbalances between the number of buyers and sellers.

In the average stock, we find a fairly low level of herding in trades by the funds. In fact, mutual funds exhibit only a slightly greater tendency to herd than pension funds (Lakonishok et al. (1992)). We also find that mutual funds are equally likely to herd when buying versus selling stocks. However, we find significantly higher levels of herding when we focus on subgroups of funds and on subgroups of stocks. Looking at subgroups of funds, we find much higher levels of herding among growth-oriented mutual funds than among income funds. This finding is consistent with growth funds possessing less precise information about the future earnings of their stockholdings (mainly growth stocks) than income funds (which hold mainly value stocks), giving growth funds a greater incentive to herd for whatever reason.

Looking at subgroups of stocks, we find a much higher level of herding in small stocks, especially on the sell-side. This finding is consistent with the funds sharing an aversion to stocks that have recently dropped significantly in price (Falkenstein (1996)).

In a further examination of subgroups of stocks, we find higher levels of herding in stocks with extreme prior-quarter returns than in other stocks. That is, herds form more often on the buy-side in high past return stocks and on the sell-side in low past return stocks, especially among growth-oriented funds. This evidence implicates the use of positive-feedback (momentum) strategies by growth-oriented funds as an important source of herding. Although selling past losers is also consistent with "window-dressing" explanations of fund trading, we find little evidence that window-dressing contributes significantly to observed levels of herding.

Our most important contribution is in analyzing the impact of mutual fund trading on long-term stock returns. Contrary to a statement by Jeff Vinik, the former manager of the Fidelity Magellan Fund, mutual funds are rewarded for "joining the herd."[7] Stocks that funds buy in herds have significantly higher abnormal returns during subsequent quarters than stocks that funds sell in herds, chiefly due to the underperformance of stocks sold by herds. For example, the next-quarter difference in abnormal returns between stocks most heavily bought and stocks most heavily sold is greater than two percent. This return difference is mainly concentrated in small stocks—and these stocks exhibit a next-quarter return difference exceeding

[7] Jeff Vinik is quoted as follows in the March 31, 1996, annual report of the fund: "I believe it's critical not to be part of the herd when investing in financial markets. Just because most investors are moving in a particular direction doesn't make it the best direction; in fact, often it has meant the opposite." This statement was made shortly after the Magellan fund reduced its technology stock holdings from nearly 40 percent to less than four percent and increased its position in bonds and short-term investments from six percent to approximately 30 percent. This shift resulted in the fund underperforming major stock indexes (which was chiefly due to the poor performance of bonds versus stocks in the portfolio).

four percent. However, large stocks also exhibit a modest return difference of approximately one percent.

Interestingly, the next-quarter return difference (between stocks bought and sold by herds) is much higher for all size fractiles during the first 10 years of our sample period (1975 to 1984), even though the mutual funds do not show a markedly higher tendency to herd during this period. In fact, only small stocks exhibit a significant next-quarter return difference during the second 10-year period (1985 to 1994).[8] Overall, any observed stock price adjustments following trading by herds appear to be permanent, supporting the idea that mutual fund herds speed the price-adjustment process and are not destabilizing. Thus, our results are most consistent with theories of herding based on private information about fundamentals (Hirshleifer et al. (1994) and Bikhchandani et al. (1992)) and not with theories of herding based on reputational concerns (Scharfstein and Stein (1990)). Of course, the limitations of our quarterly holdings data set prevent us from making conclusive statements about whether herding destabilizes daily or weekly stock prices.

In a related paper, Chan et al. (1996) find that there is little sign of return reversals for stocks with high price and earnings momentum (after the 12-month momentum effect), which suggests that the momentum effect is not induced by "irrational" positive-feedback trading strategies (those with a temporary price impact). They suggest that the momentum effect is caused by a delayed reaction of investors to the information in past returns and past earnings. Our results suggest that mutual fund herding plays a significant role in this mechanism, since herding is highly related to "rational" positive-feedback trading strategies (those with a permanent price impact) and since we find some evidence that herding provides additional cross-sectional explanatory power in predicting future stock returns after controlling for momentum in returns. Our findings, by linking momentum patterns in stock returns to trading patterns among mutual funds, provide some additional evidence supporting the idea that the momentum anomaly is not a statistical fluke.

In another related paper of interest, Warther (1995) finds that unexpected inflows of money from investors to the mutual fund industry are strongly correlated with concurrent returns on broad stock market indexes. However, there is no evidence that inflows are correlated with past returns (feedback trading) or with future returns (an impact on stock returns).[9] We test for the relation between inflows of money and herding in stocks; our results provide little evidence of any correlation between levels of herding and either expected or unexpected inflows to the mutual fund industry. Thus, feedback trading and the impact of trading on stock returns occur because of trading

[8] Other studies (e.g., Daniel et al. (1997)) also find weaker evidence of performance among mutual funds during this second 10-year period.

[9] Also, Stulz (1997) reviews studies of inflows of capital to emerging markets and concludes that there is no support for the view that inflows increase the volatility of equity returns.

decisions at the fund manager level, and not because of trading strategies at the level of those who invest in mutual funds.

The remainder of the paper is organized in three sections. The holdings database and the herding measures are described in Section I. Empirical findings are presented in Section II. We conclude the paper in Section III.

I. Methodology

A. The Mutual Fund Holdings Database

Portfolio holdings for virtually all mutual funds based in the United States which hold equities and which exist at any time between December 31, 1974 and December 31, 1994 were purchased from CDA Investment Technologies, Inc., of Rockville, Maryland. CDA does not impose any minimum survival period requirement for a fund to be included in the database. Appendix A further describes the database and the data-collection procedure used by CDA. These mutual fund data include periodic share holdings of equities for each fund; for most funds, holdings "snapshots" are available in the database at the end of each calendar quarter. We describe this issue more fully below.

Monthly returns (compounded from daily returns) and month-end prices for stocks are obtained from the CRSP daily files. Mutual fund holdings of stocks of some foreign-domiciled corporations that are traded only on foreign exchanges are included in the CDA database, especially during the last few years of the sample period. These foreign equities are chiefly Canadian stocks held by some Canadian mutual funds that CDA began to cover. Because only stocks traded on U.S. exchanges are covered by CRSP, equity holdings that are exclusively traded in foreign markets are omitted from this study.

Table I presents summary statistics for the database. To present statistics that are more representative of mutual funds that normally trade CRSP stocks, we exclude (from Panels A, B, C, and E) foreign funds, "bond and preferred" funds, and funds not providing an explicit investment objective. Panel A shows that the number of mutual funds covered in the database increases dramatically, from almost 400 to more than 2,400 during the 20-year period. Although the count of funds in every category exhibits rapid increases, the count of growth-oriented funds generally increases faster than income-oriented funds. The reader is referred to Grinblatt et al. (1995) for descriptions of the investment strategies of funds having various investment objectives.

Panel B presents the average fund size, along with the dollar proportion of fund assets that are invested in equities covered by the CRSP files. The total net assets of the average fund increase from \$99 million to \$401 million over the 20-year period. We study stock trades by mutual funds in this paper; stock holdings of CRSP stocks account for more than 70 percent of the total net assets held by the mutual fund industry during most of the study period.

Panel C shows the number of distinct stocks in the holdings database, the number of different stocks held by the average fund, the proportion of those stocks with price and return information available in the CRSP files, and the proportion of all CRSP stocks held by at least one mutual fund. Along with the rapid increase in numbers of mutual funds (Panel A), we find that the average fund invests in a broader spectrum of stocks during the later years. The average fund held 45 stocks at the beginning of 1975, doubling to 90 stocks by the beginning of 1995.[10] Given this increase in both the number and size of funds, it is not surprising that both the number of distinct stocks and the proportion of the number of available CRSP stocks held by the universe of funds dramatically increases. Of the 1,764 different stocks held by the funds in 1975, about 98 percent are covered by CRSP; these stocks represent about 38 percent of all stocks covered by CRSP in 1975. Also, the 98 percent include 76 percent that trade on the NYSE or AMEX and 22 percent that trade through Nasdaq, representing 55 percent and 19 percent of all CRSP stocks (in 1975) in those markets, respectively. By 1995, the funds held 7,703 different stocks, which represent about 77 percent of all CRSP stocks.[11] Noteworthy, also, is that funds hold increasing proportions of Nasdaq stocks (at the expense of NYSE and AMEX stocks) in their portfolios during the later years of our study period. However, because of the dramatic increase in the number of funds over the period (and in the size of the average fund), the proportion of all NYSE/AMEX and Nasdaq stocks held by the funds both increase dramatically.

Panel D presents statistics on the trades of the funds, which we infer from changes in the quarterly portfolio holdings of each fund.[12] We note here that quarterly portfolio "snapshots" miss roundtrip trades that are completed within a single quarter; however, an examination of the data suggests that such trades represent a small minority of all mutual fund trades. The average proportion of stock trades that are "buys" during the 20-year period is slightly greater than 50 percent, reflecting the inflow of money to the funds. As expected, the number of stocks that are traded increases substantially from about 1,300 during the first quarter of 1975 to about 4,000 during the final quarter of 1994. Moreover, as the mutual fund field becomes more crowded during later years, the funds tend to trade the same stocks more often. For example, only 44 stocks are traded by 30 or more funds during the first quarter of 1975, compared to 900 stocks during the fourth quarter of 1994. 24 stocks are traded by at least 200 funds during that same quarter!

[10] This increase is partially due to the increasing popularity of index funds over this time period, as well as to the increasing size of the average actively managed mutual fund.

[11] The lower proportion of stocks covered by CRSP in 1995 is due to the increasing presence of international funds and to the misclassification of some Canadian funds (by CDA) into some non-foreign fund investment objective categories (e.g., "growth").

[12] To isolate fund-initiated trading from other types of share adjustments and trades, we routinely reverse (from the end-of-quarter shareholdings) stock dividends (such as stock splits) and other changes in the number of shares outstanding that are identified by CRSP as part of a "distribution." We also exclude stocks that were newly issued within the prior year in order to focus on seasoned equities. Therefore, for example, spinoffs do not affect our measure of herding because the number of parent company shares outstanding does not change, and because the new subsidiary spinoff stock is excluded due to being a new issue.

Table I

Summary Statistics for Mutual Fund Holdings Database

Key statistics, at five-year intervals, are provided below for the mutual fund holdings database. For each column, statistics are shown at the beginning of the listed year, except as noted in this legend. The database, purchased from CDA Investment Technologies, Inc., includes periodic (usually quarterly) portfolio holdings of equities for virtually every mutual fund (with nonzero equity holdings) that existed any time between December 31, 1974 and December 31, 1994. Panel A provides counts of funds in each self-declared investment-objective category (these data are available starting June 30, 1980; the 1980 figures are end-of-year). The "Balanced or Income" category pools both types of funds together. The "International or Other" category includes funds with a stated investment objective of "international", "metals", or "venture captial special situations." Excluded in the statistics of Panels A, B, C, and E are funds not included in one of the categories in Panel A. Panel B shows the total net assets of the average mutual fund and the dollar proportion of these assets (aggregated over all funds) that are invested in stocks covered by CRSP vs. all other assets. Panel C documents the number of different stocks held by all mutual funds as a group, the average number of different stocks held by a fund, the proportion of these stocks that are covered by CRSP, and the proportion of all CRSP stocks that are represented in the holdings database. Panel D provides trading data, inferred from quarterly portfolio holdings, for the first quarter of each year (except for 1995, which contains data for the fourth quarter of 1994). The first several rows show the number of CRSP stocks that are traded by at least a given number of funds. The next rows show aggregate trading (purchases *plus* sales of all stocks by the funds, not net purchases), evaluated at the quarterly average price for each stock. Panel E shows the proportion of all funds (excluding foreign funds and a small number of funds for which CDA was unable to identify the investment objective) existing at the beginning of each year that report portfolio holdings as of that date, and the proportion that report holdings for a date within three, six, nine, and 12 months before (and including) that date (these data become available beginning June 30, 1979).

	Year				
	1975	1980	1985	1990	1995
Panel A. Fund Counts					
Number of funds in database	393	509	522	846	2,424
Aggressive Growth	NA	89	97	144	219
Growth	NA	198	217	371	1,341
Growth & Income	NA	102	124	174	385
Balanced or Income	NA	78	67	101	216
International or other	NA	42	17	56	263
Panel B. Assets and Asset Allocation					
Total net assets of average fund ($million)	98.6	119.3	184.9	311.1	401.3
Percent CRSP stocks (by value)	76.0	79.9	87.9	81.1	65.1
Percent other assets	24.0	20.1	12.1	18.9	34.9
Panel C. Stock Counts					
Number of distinct stocks in database	1,764	2,704	3,532	4,259	7,703
Average number of stocks held per fund	44.6	45.4	43.7	61.5	89.5
Percent covered by CRSP files	97.6	95.3	98.6	95.7	81.1
Percent covered by CRSP NYSE/AMEX	76.0	66.9	56.1	51.5	36.5
Percent covered by CRSP Nasdaq	21.6	28.4	42.5	44.2	44.6
Percent of all CRSP stocks	38.4	49.0	58.5	61.2	77.3
Percent of all CRSP NYSE/AMEX	55.3	69.9	89.2	86.1	82.5
Percent of all CRSP Nasdaq	18.5	28.6	40.2	44.7	73.5

Table I—*Continued*

	Year				
	1975	1980	1985	1990	1995
Panel D. Trading Statistics (First Quarter)					
Proportion of trades that are buys (percent)	56.7	49.4	56.9	49.1	61.3
Number of stocks traded by					
≥ 1 Fund	1,290	1,918	3,189	3,282	3,956
≥ 5 Funds	480	775	1,379	1,811	2,539
≥ 10 Funds	225	382	751	1,166	1,850
≥ 20 Funds	85	127	333	655	1,253
≥ 30 Funds	44	49	168	432	900
≥ 50 Funds	6	10	58	199	549
≥ 100 Funds	0	0	5	62	163
≥ 200 Funds	0	0	0	4	24
Trades ($billion), by NYSE Size Quintile					
Q-1 (Small Stocks)	0.06	0.17	1.00	1.54	5.81
	(0.9%)	(1.9%)	(3.8%)	(2.6%)	(3.3%)
Q-2	0.13	0.45	2.00	3.97	12.74
	(2.3%)	(5.1%)	(7.6%)	(6.8%)	(7.2%)
Q-3	0.34	1.11	2.78	6.79	19.38
	(5.9%)	(12.4%)	(10.5%)	(11.7%)	(11.0%)
Q-4	0.94	2.07	5.71	12.27	37.24
	(16.2%)	(23.1%)	(21.7%)	(21.1%)	(21.0%)
Q-5 (Large Stocks)	4.32	5.15	14.88	33.71	101.79
	(74.7%)	(57.5%)	(56.4%)	(57.8%)	(57.5%)
Panel E. Reporting Frequency					
Proportion of funds (percent) reporting holdings					
Up-to-date	NA	NA	74.2	66.1	22.8
Within last 3 months	NA	NA	87.8	83.6	58.0
Within last 6 months	NA	NA	97.3	97.2	88.7
Within last 9 months	NA	NA	99.8	98.7	94.0
Within last 12 months	NA	NA	100.0	99.5	98.9

We also provide information on the breakdown of mutual fund trading by the market capitalization of stocks. Here, we measure aggregate trading in a stock by summing the absolute value of changes in shareholdings across all funds and multiplying by the average quarterly price of that stock. Although the smallest three quintiles account for only about nine percent of the aggregate value of trades in the first quarter of 1975, trades in these quintiles have more recently increased to more than 20 percent of all trades. This finding contrasts with that for pension funds, where only about three percent of trades occur in the smallest three quintiles between 1985 and 1989 (Lakonishok et al. (1992)).

Panel E provides details about the reporting frequency of funds at the beginning of each five-year period. CDA attempts to update portfolio holdings at the end of each calendar quarter for all funds, using SEC-required filings along with voluntary reports generated by the funds. However, although fund families holding equities with an aggregate market value greater than \$100 million are required to report their aggregate portfolio holdings to the SEC each fiscal quarter under Section 13(f) of the Securities Exchange Act of 1934, individual funds (since 1985) are only required to report their holdings to the SEC at the end of each fiscal semiannual period under amendments to Section 30 of the Investment Company Act of 1940. Thus, since 1985, holdings for all quarters are only available for funds choosing to provide them.

Panel E shows that, with the exception of 1995, at least two-thirds of the funds report holdings on the first day of each year shown, and more than four-fifths report holdings either on that day or on a date during the fourth quarter of the prior year. For example, 74 percent of funds report holdings on January 1, 1985, and another 14 percent (for a total of 88 percent) report holdings at some point during the fourth quarter of 1984. Almost all funds (97 percent) report holdings sometime during the last half of 1984 (including January 1, 1985). For a very small fraction of funds (less than three percent in 1985), CDA obtains holdings information less frequently. These funds are usually very small funds holding small stock portfolios, so their omission does not materially impact our study. CDA has been somewhat less successful at obtaining timely quarterly portfolio holding snapshots recently because of the huge expansion in the number of funds (especially small funds) since 1990 and because of the semiannual reporting requirement that went into effect in 1985. However, even at the beginning of 1995, almost 90 percent of funds report holdings within the past six months.

To study herding, we must synchronize fund holdings. We approximate the actual holdings by moving holdings of any fund reported within a given calendar quarter to the end of that quarter. For funds not reporting during the most recent quarter, we move the most recent holdings snapshot to the end of the quarter. For example, suppose we are examining the fourth-quarter trades of funds. The majority of funds report holdings at the end of the third and fourth calendar quarters, making an approximation of their fourth-quarter trades easy. However, some funds may report holdings at the end of August and November, rather than September and December, due to their fiscal calendar. We approximate the fourth-quarter trades of these funds by differencing the November and August holdings.[13]

In the majority of this paper, herding is measured during calendar quarters. However, due to less frequent reporting by some funds, we also discuss results (where appropriate) using a semiannual measure of herding.[14]

[13] Other funds may only report holdings at the end of May and November. For these funds, we approximate fourth-quarter trading by differencing the May and November holdings. Also, we approximate third-quarter trading as zero, since holdings are not updated until November. See Appendix A for further discussion of this issue.

[14] However, both measures will underestimate herding, if present, due to the different reporting cycles of different funds. We do not think that this problem is large, however, because the majority of funds report holdings at the end of calendar quarters.

Even though the majority of our funds report holdings at the end of each calendar quarter, a caveat is in order. We label same-direction trading (inferred from changes in portfolio holdings of individual funds) in the same stock by several funds during a quarter as "herding," although having only quarterly portfolio snapshots prevents us from detecting the sequence of this trading. For example, it is quite plausible that some funds consistently follow the trades of others weeks or even months later within the same quarter.[15]

B. Measuring Herding

For our baseline tests, we use the measure of herding designed by Lakonishok et al. (1992). Letting $HM_{i,t}$ equal the measure of herding by funds into (or out of) stock i during quarter t ("stock-quarter" i,t), this measure is expressed as:

$$HM_{i,t} = |p_{i,t} - E[p_{i,t}]| - E|p_{i,t} - E[p_{i,t}]|, \tag{1}$$

where $p_{i,t}$ is the proportion of all mutual funds trading stock-quarter i,t that are buyers. Essentially, equation (1) is a simple "count" of the number of funds buying a stock during a given quarter, as a proportion of the total number of funds trading that stock-quarter, minus the expected proportion of buyers. Then, an adjustment factor, $E|p_{i,t} - E[p_{i,t}]|$, is subtracted to allow for random variation around the expected proportion of buyers under the null hypothesis of independent trading decisions by the funds.[16]

As a proxy for $E[p_{i,t}]$, we use the proportion of all stock trades by funds that are purchases during quarter t.[17] This proxy for the expected proportion of "buys" thus stays constant across all stocks during a given quarter, changing only over time. We note that using this proxy does not allow us to fully adjust for the possibility of a secular shift of fund assets into certain classes of stocks because of the large inflows of cash that occurred over this time period. For example, funds may use inflows to invest in small stocks, which

[15] Since fund holdings are publicly available within weeks after the end of a fiscal period, funds wishing to imitate the prior-period trades of other funds will have little difficulty obtaining the necessary information. However, it is not clear how funds engaging in same-period mimicry would know how their counterparts are investing. One possibility is that fund managers may, from past experience, know that their counterparts invest in stocks highly recommended by analysts. Analyst herding, for whatever reason, would then result in mutual fund herding. Trueman (1994) studies the incentives for analysts to herd in their earnings forecasts, and Welch (1996) empirically studies analyst herding. Another possibility is that the use of common investment styles results in herding; our data will allow an analysis of this potential source of herding.

[16] See Lakonishok et al. (1992) for a more detailed explanation of this herding measure.

[17] This proportion is formed by dividing the total number of times (summed over all funds and stocks) that a fund purchases a stock during quarter t by the total number of times that a fund either purchases or sells a stock during the same quarter.

then might exhibit large herding measures due to the finite number of small stocks available. However, our evidence shows that herds form as frequently on the sell-side as on the buy-side, which indicates that cash inflows do not drive our results. We also present direct tests that show little correlation between cash inflows to the mutual fund industry and herding.

Implicitly, equation (1) defines and measures herding as the tendency of a given subgroup of funds to trade a given stock together and in the same direction, for whatever reason, more often than would be expected by funds trading randomly and independently. We can measure the extent to which any subgroup of funds herds in a typical stock-quarter by averaging the above measure (the average is denoted $\overline{HM}$), calculated for that group, across all stock-quarters traded by the group. Thus, a positive and significant $\overline{HM}$ is evidence in favor of herding by funds (for whatever reason).

For a given subgroup of funds, we compute the adjustment factor $(E|p_{i,t} - E[p_{i,t}]|)$ and the proxy for $E[p_{i,t}]$ based only on trading by that subgroup. In this article, we look both at the universe of mutual funds and at investment-objective subgroups of funds.[18] We measure the tendency of a subgroup of funds (such as "growth" funds) to herd in a subset of stock-quarters with certain characteristics (such as small stocks) by averaging $HM_{i,t}$ (calculated for that subgroup of funds) over only those stock-quarters.

We use modified herding measures to segregate stocks by whether they had a higher (or lower) proportion of buyers than the average stock during the same quarter. The relation between the unconditional herding measure, $HM_{i,t}$, and these conditional herding measures, which we call the "buy herding measure," $BHM_{i,t}$, and the "sell herding measure," $SHM_{i,t}$, is described as follows:

$$BHM_{i,t} = HM_{i,t} | p_{i,t} > E[p_{i,t}], \tag{2}$$

$$SHM_{i,t} = HM_{i,t} | p_{i,t} < E[p_{i,t}]. \tag{3}$$

Averaging $BHM_{i,t}$ (denoted $\overline{BHM}$) separately from $SHM_{i,t}$ (denoted $\overline{SHM}$) is useful in analyzing herding by funds *into* stocks separately from herding *out* of stocks.[19] For example, if mutual funds tend to sell stocks in herds much

[18] We analyze subgroups of funds because it is reasonable to believe that there is less herding among the universe of funds, where a purchase by one fund is more likely to be coupled with a sale by another fund (instead of a sale by a non-mutual fund entity). Using this argument, the universe of funds is less likely to herd during the latter part of our sample period, when mutual funds became a larger part of trading. However, we *could* conceivably find herding even among the entire universe of traders, according to $\overline{HM}$, if a few traders place large orders on one side of a trade, while many traders absorb the other side.

[19] The adjustment factor $(E|p_{i,t} - E[p_{i,t}]|)$ in equation (1) is recalculated conditioned on $p_{i,t} > E[p_{i,t}]$ or on $p_{i,t} < E[p_{i,t}]$ for $BHM_{i,t}$ and $SHM_{i,t}$, respectively, again under the null hypothesis of independent trading decisions by the funds.

more frequently than they buy in herds, then $\overline{SHM}$ will be much larger than $\overline{BHM}$. These conditional measures are also useful in analyzing stock returns following buying versus selling by a herd.

II. Results

A. Overall Levels of Herding by Mutual Funds

In Table II we present the overall levels of herding exhibited by our sample of mutual funds. The herding measure of 3.4 percent shown in Panel A is $\overline{HM}$ computed over all stock-quarters (covered by CRSP) during the 20-year period that were traded by at least five funds. We impose a hurdle of five funds trading a given stock-quarter to convey a sensible concept of a "herd," as only two or three funds trading in the same direction do not seem to qualify as a herd. Nevertheless, in a previous version of this paper we show herding measures averaged over all stock-quarters traded by at least one fund, with little difference in results.

We can think of this average herding measure as meaning that if 100 funds trade a given stock-quarter, then approximately three more funds trade on the same side of the market than would be expected if each fund randomly and independently chose stocks. This overall average level of herding (3.4 percent) does not seem particularly large; in fact, it is only slightly higher than that reported by Lakonishok et al. (1992) for their sample of pension funds (2.7 percent).

We might believe that herding, if present, would be more likely to occur when large numbers of funds trade a stock; perhaps a bigger herd makes for a stronger herd. However, our results tell a different story: herding does not monotonically increase, and actually slightly decreases as trading activity by funds increases. The average level of herding decreases to just over three percent among stock-quarters traded by 50 or more funds. We note here that stocks traded by large numbers of funds are generally large-capitalization stocks, which, as we show, exhibit lower levels of herding. The effect of changing the focus to larger stocks hides any increase in herding that might result from increased numbers of funds trading the stocks.[20]

Panel A also presents average levels of herding for investment-objective subgroups. Here, a fund is categorized by its self-declared objective at the beginning of each quarter; these data are available beginning June 30, 1980. In general, growth-oriented funds show a greater tendency to herd than income-oriented funds. This finding is consistent with growth funds investing proportionately much more money than income funds in stocks of high-growth firms. Precise information about future earnings for such firms

[20] We find some evidence, in unreported results, of increased levels of herding in small stocks as the number of funds trading these stocks increases. But, the sample sizes become very small as we increase the trading hurdle for small stocks. For example, very few small stocks experience trades by 50 or more funds in a given quarter during our sample period.

Table II

Mean Herding Measures ($\overline{HM}$ in percent)
(With number of stock-quarters in parentheses)

The herding measure, HM_{it}, for a given stock-quarter equals $|p_{i,t} - E[p_{i,t}]| - E|p_{i,t} - E[p_{i,t}]|$, where $p_{i,t}$ equals the proportion of funds trading stock i during quarter t that are buyers. Stocks included are all that have price/return information available in the CRSP files, excluding new issues for one year after their first offering date. The proxy used for $E[p_{i,t}]$ is the proportion of all stock trades by mutual funds during quarter t that are buys. $E|p_{i,t} - E[p_{i,t}]|$ is calculated under the null hypothesis of herding only by random chance. Presented in Panel A are values of $\overline{HM}$, which is HM_{it} (computed for the group of funds indicated by the row heading for each stock-quarter) averaged across all stock-quarters traded by the number of funds (in that group) indicated by the column heading. For example, the value of $\overline{HM}$ shown in the second row, first column, is HM_{it} (calculated for the group of aggressive growth funds only) averaged over all stock-quarters traded by at least five aggressive growth funds. Presented in Panel B is $\overline{HM}$ computed over five-year subperiods. Note that the total number of stock-quarters summed across investment-objective categories differs from that for the universe of funds, since one stock-quarter may be traded by, e.g., more than five aggressive growth funds and more than five growth funds (or, alternatively, by three aggressive growth and two growth funds). All fund categories are based on self-declared investment objectives at the beginning of each quarter; these data are available beginning June 30, 1980. Due to the large sample sizes, all t-statistics are highly significant.

Panel A. 1975–1994

	Number of Trades				
Fund Category	≥5	≥10	≥20	≥30	≥50
All funds	3.40 (109,486)	3.61 (67,252)	3.41 (34,704)	3.29 (21,571)	3.17 (10,461)
Aggressive Growth	3.98 (20,423)	3.55 (5,458)	4.01 (645)	3.75 (81)	— (0)
Growth	2.87 (55,308)	2.24 (28,817)	2.02 (12,691)	1.94 (6,895)	2.00 (2,487)
Growth & Income	1.63 (22,079)	1.62 (9,476)	1.85 (2,492)	1.40 (785)	0.68 (94)
Balanced or Income	1.91 (10,203)	1.20 (3,362)	0.85 (579)	1.42 (128)	2.79 (5)
International or other	4.10 (15,757)	4.16 (6,569)	4.28 (2,062)	5.46 (940)	5.20 (214)

Panel B. Subperiods, for #Trades ≥ 5

Fund Category	1975–1979	1980–1984	1985–1989	1990–1994
All funds	4.00 (13,820)	3.21 (18,759)	3.33 (31,253)	3.35 (45,654)
Aggressive Growth	NA	3.72 (2,567)	3.90 (5,607)	4.08 (12,249)
Growth	NA	3.75 (6,950)	3.28 (17,418)	2.45 (30,940)
Growth & Income	NA	2.34 (3,531)	1.47 (7,782)	1.52 (10,766)
Balanced or Income	NA	3.21 (446)	2.11 (2,187)	1.78 (7,570)
International or other	NA	3.40 (2,141)	4.49 (5,698)	4.00 (7,918)

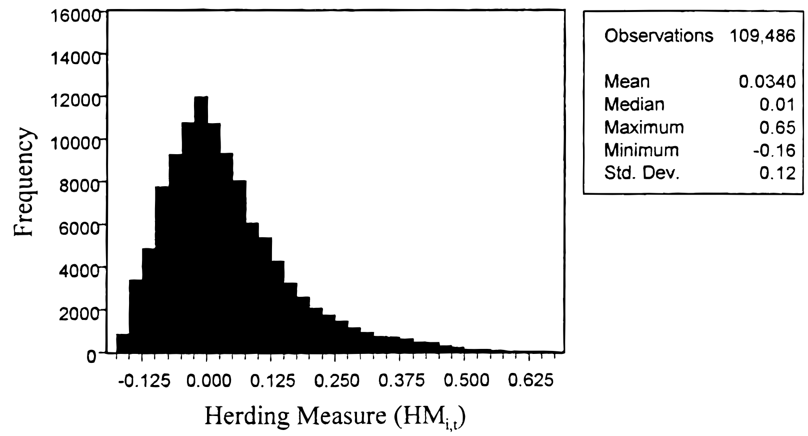
is usually more difficult for analysts to obtain, which may lead to funds trading together for reasons other than information about fundamentals (e.g., Scharfstein and Stein (1990)), or it may lead to information-disadvantaged funds systematically disregarding their imprecise private information and following the prior trades of their better-informed counterparts (e.g., Bikhchandani et al. (1992)). This finding is also consistent with growth funds being more heavily invested in small stocks and, thus, being more sensitive to the changing characteristics of these stocks (Falkenstein (1996)). We present tests in later sections that further explore these possibilities.

Aggressive growth funds, for example, exhibit a level of herding roughly twice that of growth & income or income funds. Interestingly, specialty funds show the greatest tendency to herd, as reflected in the "International or other" category. However, the results presented in Panel A reflect only stocks covered by CRSP that are traded by these funds.

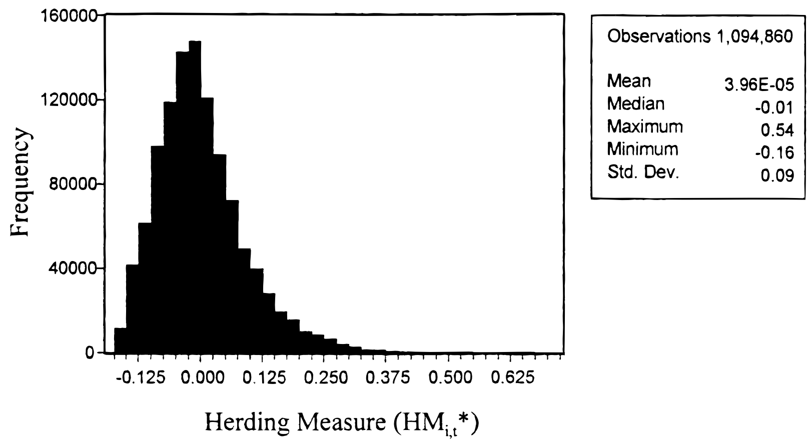
Surprisingly, $\overline{HM}$ computed for the universe of funds is not significantly lower, and, in many cases, is higher than the same measure computed for the subgroups. This finding seems unusual because we might think that funds with the same objective would trade together more often than would a heterogeneous group of funds. However, this conjecture is not supported by the evidence—herds form as often across different stylistic categories as they do within the same category. One potential reason is that we may be picking up "herding" by funds belonging to the same fund family but having different stated investment objectives. A second potential reason is that a common investing style being used by funds in different stylistic categories results in herding. For example, Grinblatt et al. (1995) find that 77 percent of a sample of funds use a positive-feedback trading strategy. We explore the first possibility later in this section, and the second in Sections B and C.

Figure 1 compares the distributions of actual and simulated stock-quarter herding measures ($HM_{i,t}$ and $HM^*_{i,t}$). Ten simulated measures are generated for each actual stock-quarter in our sample. Each simulated measure is generated assuming that the actual funds trading that stock-quarter each make a decision to buy or sell independently of the buy or sell decision of other funds (i.e., funds herd only by chance); Monte Carlo simulation details are provided in Appendix B. The resulting histogram is a (simulated) mixture of distributions, each distribution corresponding to a specific stock-quarter and represented by a sample of ten simulated outcomes.

The figure compares the actual to the simulated distribution for stock-quarters traded by at least five funds. The actual distribution (Panel A) has a substantially greater probability mass on large herding outcomes (a fatter right tail) than the simulated distribution (Panel B), reflecting the tendency of the funds to exhibit herding behavior above that due to random chance. Further, a comparison of the two histograms indicates that, to some extent, our finding of herding is being driven by a minority of stocks. Indeed, similar to the Lakonishok et al. (1992) study, the median actual herding mea-



Panel A: Actual Distribution



Panel B: Simulated Distribution

Figure 1. Distributions of Actual and Simulated Herding Measures. This figure presents histograms of actual and simulated herding measures ($HM_{i,t}$ and $HM^*_{i,t}$) calculated for each stock-quarter during the period 1975 to 1994. A stock-quarter is included in each histogram if it has price and return information available in the CRSP files (excluding stocks that were new issues within the year prior to the quarter under study), and if it is actually traded by at least five mutual funds. The actual herding measure, HM_{it}, for a given stock-quarter equals $|p_{i,t} - E[p_{i,t}]| - E|p_{i,t} - E[p_{i,t}]|$, where $p_{i,t}$ equals the proportion of funds buying stock i during quarter t among all funds trading that stock during that quarter. The proxy used for $E[p_{i,t}]$ is the proportion of all stock trades by mutual funds during quarter t that are purchases. $E|p_{i,t} - E[p_{i,t}]|$ is calculated under the null hypothesis of herding only by random chance. The simulated herding measure, $HM^*_{i,t}$, equals $|p^*_{i,t} - E[p^*_{i,t}]| - E|p^*_{i,t} - E[p^*_{i,t}]|$, where $p^*_{i,t}$ is computed by taking a random draw from a binomial distribution, $b(n_{i,t}, p_t)$, then dividing the draw by $n_{i,t}$. Here, $n_{i,t}$ is the number of mutual funds actually trading stock-quarter i,t, and p_t is the proportion of funds in the population that, should they trade stock-quarter i,t, would be buyers (under the null hypothesis). The proxy used for p_t (which also equals $E[p^*_{i,t}]$) is also the proportion of all stock trades by mutual funds during quarter t that are purchases. Ten simulated draws are taken for each stock-quarter.

sure is much lower than the mean. We find similar results when comparing actual and simulated herding measure distributions for stock-quarters traded by larger numbers of funds.

Panel B of Table II shows average herding levels ($\overline{HM}$) over five-year subperiods. In general, mutual fund herding does not appear to change much over the 20-year period.

As discussed in a previous section, a minority of funds report holdings only twice per year. Thus, it is likely that our computed levels of herding are understated because of the incomplete trading information for these funds when using a calendar quarter frequency. In unreported tests, we recompute the herding measures using a semiannual period as our unit of time measurement. The results do show slightly higher levels of herding, although not dramatically so. The universe of funds exhibits an average herding level of 5.1 percent, measured semiannually, as opposed to 3.4 percent, measured quarterly. Investment-objective subgroups show analogous results.

Another way to look at the data is to use the fund family (instead of individual funds) as the primary unit of measurement. As mentioned previously, our finding of herding in Table II could simply be a result of funds within the same family investing together; for example, all of the various Fidelity funds may invest similarly because they may be exposed to the same research or they may incur lower unit trading costs by trading together. If so, we would expect to find a lower level of herding using the fund family as our measurement unit.

Table III investigates this issue. To compute our measure of herding ($HM_{i,t}$) using the fund family as the measurement unit, we sum holdings over all funds within the same management company. If the cumulative shareholdings of a given stock increase (decrease) during a given quarter, controlling for exogeneous changes in the supply of the stock (e.g., stock splits), the fund family is considered to have been a buyer (seller) of the stock.

The results show a decrease in the level of herding, which is consistent with funds within the same family trading together. However, we still find significant herding across different fund families. Roughly two percent more fund families, on average, are on the same side of trading than expected, while approximately three to four percent more individual funds (Table II) are on the same side than expected. Herding, measured across fund families, does not increase with larger numbers of families trading a given stock-quarter, nor does it vary much across five-year subperiods. Since we do find a lower level of herding using the fund family as the unit of measurement, we discuss results in later sections computed in this manner when appropriate; however, for all of our remaining tests, we use individual funds as our primary unit of measure. In general, we show that our evidence relating mutual fund herding with changes in stock prices is not materially affected by the unit of measurement; results are only slightly weaker when the fund family is the unit.

Finally, we recompute our measures of herding (using individual funds as the unit of measurement), excluding any trade of a stock-quarter by a fund that has a dollar value less than 0.1 percent of the total net assets of that

Table III

Mean Herding Measures ($\overline{HM}$ in percent), for Mutual Fund Management Companies (With number of stock-quarters in parentheses)

The herding measure, HM_{it}, for a given stock-quarter equals $|p_{i,t} - E[p_{i,t}]| - E|p_{i,t} - E[p_{i,t}]|$, where $p_{i,t}$ equals the proportion of management companies trading stock-quarter i,t that are buyers. A management company is considered to have bought (sold) stock-quarter i,t if the net trading by all funds in that family amounts to a purchase (sale). Stocks included are all that have price/return information available in the CRSP files, excluding new issues for one year after their first offering date. The proxy used for $E[p_{i,t}]$ is the proportion of all stock net trades by management companies during quarter t that are purchases. $E|p_{i,t} - E[p_{i,t}]|$ is calculated under the null hypothesis of herding only by random chance. Presented below are values of $\overline{HM}$, which is HM_{it} averaged across stock-quarters with non-zero net trades for the number of management companies indicated in the column heading. For example, the value shown in the second row, first column, is $\overline{HM}$ for 1975–1979, which is averaged across all stock-quarters having non-zero net trades for at least five management companies. Due to the large sample sizes, all t-statistics are highly significant.

	Number of Trades			
	≥5	≥10	≥20	≥30
1975–1994	2.22 (101,729)	2.12 (56,833)	2.08 (24,806)	2.14 (13,190)
1975–1979	2.33 (13,069)	2.55 (5,791)	3.28 (1,646)	3.43 (596)
1980–1984	1.96 (17,229)	2.02 (7,833)	2.20 (2,224)	2.34 (807)
1985–1989	2.32 (28,278)	2.38 (15,059)	2.21 (6,011)	2.49 (2,898)
1990–1994	2.23 (43,153)	1.93 (28,150)	1.87 (14,925)	1.92 (8,889)

fund at the beginning of the quarter. This exercise is done to determine whether our measure of herding mainly reflects the tendency of several funds to make small portfolio adjustments in the same direction at the same time. For example, index funds might all make similar adjustments as stocks are added or dropped from the index. The (unreported) results show that levels of herding are even higher when looking only at trades that exceed this 0.1 percent hurdle.

B. Herding Segregated by the Characteristics of Stocks

Our overall herding results of the last section indicate that levels of herding by mutual funds in the average stock-quarter are not very large, and are roughly equal to levels of herding found in a prior study of pension funds. Growth-oriented funds, however, show a greater tendency than other funds to herd. To investigate potential explanations for this finding, we next examine levels of herding in subgroups of stocks with certain characteristics. Moreover, we look at whether herding occurs more often on the buy-side or sell-side of mutual fund trading.

B.1. Herding in Small versus Large Stocks

One meaningful way to look at the data is to partition stock-quarters by market capitalization. We examine the data in this manner because most theories would predict higher levels of herding in the stocks of small, high-growth firms. As mentioned previously, fund managers probably receive lower precision earnings information from these companies and are more likely to disregard this information if the consensus opinion is different; alternatively, fund managers may share an aversion to holding small stocks (e.g., because these stocks are less liquid).

In Panel A of Table IV, we present herding measures averaged over stock-quarters segregated by market capitalization. Size quintile breakpoints, which are used to classify all CRSP stocks, are determined by ranking NYSE stocks only; these breakpoints are updated at the beginning of each calendar quarter. In addition to presenting average levels of herding ($\overline{HM}$), we present average buy-herding ($\overline{BHM}$) and sell-herding ($\overline{SHM}$) measures for each size quintile to determine whether herds tend to form more often on one side of the market.

Looking first at the universe of funds ("All funds"), we find that herds form much more often on the sell-side ($\overline{SHM}$) than on the buy-side ($\overline{BHM}$) in trades of small stocks (S1), but that levels of buy-side and sell-side herding are roughly equivalent among larger stocks (S2–S5).[21] In fact, we find our most compelling evidence of herding in sales of small stocks by growth-oriented funds: eight to nine percent more aggressive growth and growth funds tend to be sellers than we would expect from funds that trade randomly and independently of each other. Specialty ("International or other") funds also show significant levels of herding in small stocks, although they seldom trade such stocks.

Growth-oriented funds form herds more frequently when buying small stocks (as opposed to larger stocks) as well, although the level (three to four percent) is much lower than the level on the sell-side. In unreported results, we find much higher levels of herding when funds trade the smallest subgroup of stocks falling within quintile S1. For example, stocks belonging to the smallest 25 percent subfractile of quintile S1 exhibit a sell-herding measure of about 25 percent among all funds. However, we note that only about 20 stocks per quarter are that small and are traded by at least five funds.

Our finding of higher levels of herding among growth-oriented mutual funds (especially in trades of small stocks) is not very surprising, given the nature of the stocks these funds predominantly trade. As mentioned in Section A, the observed levels of herding among these funds could be consistent

[21] This finding counters concerns by Wylie (1997) that a significant $\overline{HM}$ herding measure may result, in the absence of herding, solely from biases in the measure that are due to short-sale constraints of mutual funds. In that case, we would expect buy-side herding to be stronger than sell-side herding.

Table IV

Buy- and Sell-Herding Measures ($\overline{BHM}$ and $\overline{SHM}$ over 1975–1994, in percent), Segregated by Size or Prior-Quarter Return Quintiles (With number of stock-quarters in parentheses below the measure)

The herding measure, HM_{it}, for a given stock-quarter equals $|p_{i,t} - E[p_{i,t}]| - E|p_{i,t} - E[p_{i,t}]|$, where $p_{i,t}$ equals the proportion of funds trading stock i during quarter t that are buyers. Stocks included are all that have price/return information available in the CRSP files, excluding new issues for one year after their first offering date. The proxy used for $E[p_{i,t}]$ is the proportion of all stock trades by mutual funds during quarter t that are buys. $E|p_{i,t} - E[p_{i,t}]|$ is calculated under the null hypothesis of herding only by random chance. Presented in Panel A are values of $\overline{HM}$ (in rows labelled "Total"), which is HM_{it}, averaged across all stock-quarters traded by at least five funds. Also presented are $\overline{BHM}$ and $\overline{SHM}$ (in rows labelled "Buy" and "Sell," respectively), which are average values of HM_{it} conditioned on $p_{i,t} > E[p_{i,t}]$ and $p_{i,t} < E[p_{i,t}]$, respectively. These herding measures are averaged separately over stock-quarters belonging to different market capitalization quintiles (using NYSE market capitalization breakpoints at the beginning of the quarter for which the herding measure is calculated for a stock). Panel B presents similar statistics, except that stock-quarters are now segregated by the return quintile that they belonged to during the quarter prior to the herding measurement quarter (prior-quarter return breakpoints are based on the universe of NYSE and AMEX stocks). Note that the total number of stock-quarters summed across investment-objective categories differs from that for all funds, since one stock-quarter may be traded by, e.g., more than five aggressive growth funds and more than five growth funds (or, alternatively, by three aggressive growth and two growth funds). All fund categories are based on self-declared investment objectives at the beginning of each quarter; these data are available beginning June 30, 1980. Categories containing fewer than 100 stock-quarters are marked "NA." In all other cases, t-statistics are highly significant. Note that the average measure in the "Total" category does not equal the weighted average "Buy" and "Sell" categories because "Buy" and "Sell" are average conditional herding measures. Also, averages across S1 through S5 (Panel A) are slightly different than averages across R1 through R5 (Panel B) because Panel A requires that market capitalization information be available, while Panel B requires that past returns be available. Any differences between the panels are chiefly due to incomplete data in the CRSP files for some small, thinly-traded stocks.

Panel A. Mean Herding Measures, by Size Quintile

Fund Category	Direction of Trade	S1 (Small Stocks)	S2	S3	S4	S5 (Large Stocks)	Total
All funds	Buy	3.65	3.07	3.02	2.87	2.51	2.98
		(7,692)	(12,079)	(12,151)	(11,876)	(11,240)	(55,038)
	Sell	8.10	3.19	2.87	2.82	2.75	3.73
		(8,628)	(11,179)	(11,163)	(11,401)	(12,077)	(54,448)
	Total	6.17	3.15	2.98	2.89	2.66	3.40
		(16,320)	(23,258)	(23,314)	(23,277)	(23,317)	(109,486)
Aggressive Growth	Buy	4.36	3.10	3.30	3.13	2.86	3.20
		(727)	(2,637)	(2,691)	(1,734)	(2,116)	(9,905)
	Sell	9.05	3.43	3.68	4.68	4.04	4.40
		(985)	(2,422)	(2,617)	(2,061)	(2,433)	(10,518)
	Total	7.46	3.32	3.64	4.14	3.70	3.98
		(1,712)	(5,059)	(5,308)	(3,795)	(4,549)	(20,423)
Growth	Buy	3.00	2.31	2.55	2.52	1.98	2.39
		(2,119)	(5,098)	(6,603)	(7,135)	(7,244)	(28,199)
	Sell	8.41	2.74	2.62	2.69	3.05	3.26
		(2,236)	(4,474)	(5,853)	(6,460)	(8,086)	(27,109)
	Total	5.86	2.57	2.65	2.65	2.59	2.87
		(4,355)	(9,572)	(12,456)	(13,595)	(15,330)	(55,308)
Growth & Income	Buy	NA	4.01	1.30	1.44	1.52	1.51
			(144)	(1,018)	(3,410)	(6,940)	(11,532)
	Sell	NA	5.64	2.23	1.10	1.42	1.68
			(184)	(981)	(3,044)	(6259)	(10,547)
	Total	NA	5.78	1.86	1.29	1.49	1.63
			(328)	(1,999)	(6,454)	(13,199)	(22,079)
Balanced or Income	Buy	NA	NA	3.73	2.13	1.47	1.78
				(284)	(1,279)	(3,900)	(5,496)
	Sell	NA	NA	6.23	3.22	0.95	2.02
				(259)	(1,100)	(3,277)	(4,707)
	Total	NA	NA	4.92	2.52	1.30	1.91
				(543)	(2,379)	(7,177)	(10,203)
International or other	Buy	7.08	4.47	4.78	3.52	3.05	3.60
		(190)	(618)	(1,136)	(1,882)	(4,287)	(8,113)
	Sell	23.95	5.17	4.39	4.11	3.04	4.39
		(282)	(546)	(1,012)	(1,766)	(4,038)	(7,644)
	Total	17.73	4.99	4.71	3.90	3.13	4.10
		(472)	(1,164)	(2,148)	(3,648)	(8,325)	(15,757)

Table IV—*Continued*

Panel B. Mean Herding Measures, by Prior-Quarter Return Quintile

Fund Category	Direction of Trade	R1 (Low Return)	R2	R3	R4	R5 (High Return)	Total
All funds	Buy	2.16	2.70	3.00	3.04	3.68	2.98
		(8,324)	(10,482)	(10,869)	(12,363)	(13,019)	(55,057)
	Sell	5.36	3.38	3.06	2.99	3.82	3.74
		(10,993)	(10,583)	(10,151)	(11,092)	(11,635)	(54,454)
	Total	4.10	3.11	3.07	3.03	3.77	3.41
		(19,317)	(21,065)	(21,020)	(23,455)	(24,654)	(109,511)
Aggressive Growth	Buy	2.12	2.25	2.85	3.39	4.00	3.21
		(1,400)	(1,390)	(1,342)	(2,053)	(3,716)	(9,901)
	Sell	6.35	4.97	4.17	3.76	2.98	4.39
		(2,377)	(1,752)	(1,542)	(1,920)	(2,927)	(10,518)
	Total	5.09	4.01	3.81	3.67	3.60	3.98
		(3,777)	(3,142)	(2,884)	(3,973)	(6,643)	(20,419)
Growth	Buy	1.80	2.17	2.40	2.59	2.71	2.39
		(4,065)	(5,479)	(5,548)	(6,503)	(6,616)	(28,211)
	Sell	4.59	2.96	2.74	2.62	3.57	3.27
		(4,828)	(5,124)	(5,133)	(6,047)	(5,978)	(27,110)
	Total	3.42	2.63	2.61	2.68	3.12	2.87
		(8,893)	(10,603)	(10,681)	(12,550)	(12,594)	(55,321)
Growth & Income	Buy	2.33	1.37	1.85	1.51	0.68	1.52
		(1,420)	(2,592)	(2,685)	(2,950)	(1,903)	(11,550)
	Sell	0.84	1.55	1.07	1.81	2.70	1.68
		(1,213)	(2,010)	(2,287)	(2,787)	(2,260)	(10,557)
	Total	1.67	1.44	1.52	1.66	1.93	1.63
		(2,633)	(4,602)	(4,972)	(5,737)	(4,163)	(22,107)
Balanced or income	Buy	1.51	1.83	1.67	1.93	1.74	1.76
		(622)	(1,195)	(1,282)	(1,428)	(989)	(5,516)
	Sell	2.72	1.65	0.78	1.87	3.44	2.01
		(592)	(909)	(1,036)	(1,247)	(943)	(4,727)
	Total	2.00	1.72	1.28	1.90	2.60	1.91
		(1,214)	(2,104)	(2,318)	(2,675)	(1,932)	(10,243)
International or other	Buy	3.33	3.71	3.30	3.34	4.25	3.60
		(1,225)	(1,583)	(1,656)	(1,949)	(1,703)	(8,116)
	Sell	5.65	4.04	4.00	3.72	4.79	4.39
		(1,361)	(1,618)	(1,525)	(1,703)	(1,450)	(7,657)
	Total	4.69	4.03	3.75	3.59	4.60	4.09
		(2,586)	(3,201)	(3,181)	(3,652)	(3,153)	(15,773)

with theories of herding based on reputational concerns of fund managers or with theories of herding based on funds having differential precision of information about fundamentals. Positive-feedback trading strategies, which we investigate in the next section, are also consistent with either group of theories. Therefore, a further exploration of the motivation for herding requires an examination of the long-term returns following trading by herds, which we explore in Section C.

Before proceeding, we note that the dramatically higher levels of herding on the sell-side in small stocks are also consistent with the idea that mutual funds share a strong aversion to small stocks (Falkenstein (1996)), so they tend to sell stocks that have recently fallen in price. However, the high levels of herding among funds trading stocks in portfolio S1 do not unduly impact our overall levels of herding because stocks in S1 represent fewer than 20 percent of all stocks traded by at least five funds.

B.2. Herding in High versus Low Past-Return Stocks

The second way that we partition stock-quarters is by past returns; this is done to investigate the tendency of funds to trade together due to common feedback strategies. As mentioned previously, positive-feedback trading strategies are widely used by mutual funds (Grinblatt et al. (1995)) and can be either stabilizing or destabilizing to stock prices. Alternatively, funds may herd due to "window-dressing" strategies (Lakonishok et al. (1991)), which amount to selling past losers.

In Panel B of Table IV, we segregate stock-quarters by the return quintile they belonged to during the quarter immediately prior to the herding measurement quarter. In this way, we determine whether herding is more common in stocks having high or low past returns. Prior-quarter return breakpoints are based on all NYSE and AMEX stocks; these breakpoints are updated and are used to classify all CRSP stocks (traded by five funds or more) at the beginning of each quarter.

Focusing first on the universe of funds ("All funds"), we find that levels of herding are slightly higher among stocks having extreme prior-quarter returns (R1 and R5). Buy herding ($\overline{BHM}$) is strongest in high prior-quarter return stocks (R5), and sell herding ($\overline{SHM}$) is strongest in low prior-quarter return stocks (R1). These results are consistent with the funds investing in many of the same stocks (by choice or by chance) as they execute positive-feedback trading strategies. Interesting to note is that the funds buy high prior-quarter return stocks more frequently than they sell low prior-quarter return stocks—that is, positive-feedback strategies most frequently involve buying past winners.

Although selling losers is also consistent with window-dressing explanations, we find (in unreported results) little variation in levels of sell-side herding across calendar quarters. The average level of herding in the fourth quarter (the end of the fiscal year for most funds) is similar to the average level in other quarters, indicating that window-dressing is not a major contributor to herding.

This positive correlation between the direction of herding and the magnitude of past returns is only present among aggressive growth and growth funds; growth & income and balanced/income funds tend to exhibit a negative correlation (i.e., they exhibit negative feedback trading strategies). In unreported results, we find an even stronger relation for growth-oriented funds between *same-quarter* returns and the direction of herding. For example, aggressive growth funds exhibit a level of buy-side herding (3.5 percent) in same-quarter "winners" that is much larger than the level (0.1 percent) in "losers." Sell-side herding in losers (8.1 percent) is similarly much larger than that in winners (2.5 percent). Since growth-oriented funds exhibit a greater tendency to use positive-feedback strategies (Grinblatt et al. (1995)), it is apparent that these strategies are contributing significantly to herding by the mutual fund industry and that funds using such strategies respond quickly (i.e., during the same quarter) to stocks exhibiting extreme returns.

B.3. Trading Imbalances Measured in Dollars

Another way to look at the trades of mutual funds is to examine, for a given stock-quarter, the excess of purchases (in dollars) over sales. As Lakonishok et al. (1992) point out, feedback trading strategies could have a bigger impact on stock prices if positive-feedback traders tend to make larger trades than negative-feedback traders. We use the "dollar ratio" trade imbalance measure used by Lakonishok et al. (1992),

$$Dratio_{i,t} = \frac{\$buys_{i,t} - \$sells_{i,t}}{\$buys_{i,t} + \$sells_{i,t}}, \tag{4}$$

where $\$buys_{i,t} - \$sells_{i,t}$ is the aggregate net increase in dollar holdings of stock-quarter i, t by all fund managers who trade it. We apply the average stock i price during quarter t to both beginning- and end-of-quarter shareholdings to control for changes in holdings that result from stock price changes. For ease of comparison with earlier results, we again limit our analysis to stock-quarters traded by at least five mutual funds.

Table V presents the *Dratio* measure, averaged across stock-quarters falling into different prior-quarter return and beginning-of-quarter size quintiles. Consistent with prior findings, mutual funds move dollars into high past-return stocks and out of low past-return stocks, especially in trades of small stocks. The highest past-return stocks (R5) falling into the smallest two quintiles (S1 and S2) exhibit roughly 20 percent more increases than decreases in fund dollar holdings, while the lowest past-return stocks (R1) in those size quintiles exhibit slight dollar decreases in holdings.

This positive correlation between past returns and current dollar trade imbalances is weaker, but still present, for larger stocks. Here, our results depart significantly from those for pension funds, which follow positive-feedback strategies only in the smallest two quintiles of stocks. In the second largest size quintile (S4), for example, mutual fund purchases exceed

Table V

Dollar-Ratio Trade Imbalance Measures, Segregated by Size and Prior-Quarter Return Quintiles (With number of stock-quarters in parentheses below the measure)

The dollar-ratio trade imbalance measure for a stock-quarter equals $(\$buys_{i,t} - \$sells_{i,t})/(\$buys_{i,t} + \$sells_{i,t})$, where $\$buys_{i,t}$ $(\$sells_{i,t})$ equals the total purchases (sales) by all mutual funds, in dollars, of stock i during quarter t (applying the average of the beginning- and end-of-quarter prices to aggregate increases (decreases) in shareholdings for that stock-quarter). Stock-quarters included are all that have price/return information available in the CRSP files, excluding new issues for one year after their first offering date. Presented in this table are dollar-ratio measures, averaged across all stock-quarters from 1975 to 1994 traded by at least five funds. These trade imbalance measures are separately averaged over (1) the return quintile that the stock belonged to during the quarter prior to the trade imbalance measurement quarter (prior-quarter return breakpoints are based on the universe of NYSE and AMEX stocks), and (2) the market capitalization quintile that the stock belonged to at the beginning of the trade imbalance measurement quarter (breakpoints for market capitalization quintiles are based on the universe of NYSE stocks). Note that column and row totals of the number of stock-quarters in this table are slightly different than totals in Table IV due to the requirement that *both* market capitalization and prior-quarter returns be available for a stock-quarter to be included in a cell in this table. Any differences between the tables are chiefly due to incomplete data in the CRSP files for some small, thinly-traded stocks. Due to the large sample sizes, all t-statistics are highly significant.

	Market Capitalization Quintile					
Prior-Quarter Return Quintile	S1 (Small Stocks)	S2	S3	S4	S5 (Large Stocks)	Total
R1 (Lowest)	−0.050	−0.023	−0.003	−0.008	−0.023	−0.024
	(5,085)	(4,832)	(3,621)	(3,055)	(2,717)	(19,310)
R2	0.073	0.082	0.063	0.040	0.010	0.051
	(2,837)	(4,244)	(4,470)	(4,704)	(4,801)	(21,056)
R3	0.125	0.106	0.079	0.041	0.022	0.065
	(2,173)	(3,832)	(4,492)	(5,065)	(5,451)	(21,013)
R4	0.165	0.133	0.097	0.063	0.037	0.088
	(2,457)	(4,395)	(5,074)	(5,506)	(6,015)	(23,447)
R5 (Highest)	0.201	0.173	0.128	0.076	0.028	0.122
	(3,752)	(5,955)	(5,657)	(4,947)	(4,333)	(24,644)
Total	0.085	0.097	0.079	0.047	0.019	0.064
	(16,304)	(23,258)	(23,314)	(23,277)	(23,317)	(109,470)

sales by almost eight percent among stocks in the highest past-return quintile (R5), but roughly equal sales in the lowest past-return quintile (R1). The largest size quintile (S5) also shows a relation, although it is weak.

B.4. Herding and Mutual Fund Sales/Redemptions

It is possible that funds herd in response to sudden increases in new cash to be invested or investor redemptions to be satisfied; perhaps they are simply buying more of (or selling) the same stocks they already hold in common. For example, perhaps herding is driven by index funds that all buy or sell the same stocks in response to cash inflows or outflows. In a related study, Warther (1995) finds that returns on broad stock market indexes are positively correlated, contemporaneously, with unexpected inflows of money into the mutual fund industry.

In order to determine whether herding by funds is being driven by cash inflows or outflows, we run time-series regressions of the cross-sectional average herding measure ($\overline{HM}$, computed across all stocks for a given quarter) on the various measures of cash inflows and lagged inflows used by Warther (1995). Average buy-herding ($\overline{BHM}$) and sell-herding ($\overline{SHM}$) measures are also separately regressed on these various inflow measures. If funds preferentially buy (sell) certain stocks in common as a response to large amounts of cash flowing into (out of) the fund industry, then we should observe subgroups of stocks with large trade imbalances (among the funds) whenever large cash inflows or outflows occur. This activity would result in a higher average herding measure during periods that have large cash inflows or outflows.

Although we do not report these regressions, we find little evidence of any significant impact of flows on the tendency of the mutual fund industry to herd. This finding is robust to the use of cash inflows or lagged cash inflows, and to the use of expected or unexpected inflows as explanatory variables.

To sum up our evidence on the tendency of mutual funds to herd, we find that average levels of herding are not particularly large. However, herding is significantly higher in trades of small stocks (especially on the sell-side), in trades of stocks with extreme prior-quarter returns, and in trades of all stocks by growth-oriented funds. The high levels of herding in these groups of stocks may cause a large stock price adjustment, even though the low level of herding experienced by the average stock likely has very little price impact. To address this issue, in Section C we investigate whether stocks experiencing high levels of herding exhibit a significant price adjustment, and whether any such price adjustment is temporary or permanent.

C. Does Mutual Fund Herding Destabilize Stock Prices?

C.1. The Relation between Herding and Stock Returns

As discussed previously, herding and positive-feedback trading may be either stabilizing or destabilizing to stock prices. To explore this issue, we examine the relation between herding and both contemporaneous and future stock returns, and we investigate the relation between herding and past returns to further determine the extent to which herding is related to feedback trading strategies.

Our procedure is as follows. Stocks traded by at least five funds during a given quarter are subdivided into two groups: (1) those having a greater proportion of mutual fund buyers and (2) those having a greater proportion of mutual fund sellers than the average stock (traded by mutual funds) during that quarter. Then, we calculate the buy-herding (sell-herding) measure, $BHM_{i,t}$ ($SHM_{i,t}$), for each stock falling into the first (second) subgroup.

Next, stocks in the buy-herding subgroup are ranked by $BHM_{i,t}$, and quintile portfolios are formed. Thus, the top quintile portfolio (B1) contains stocks that the funds most strongly buy in herds (that quarter), and the bottom portfolio (B5) contains stocks with only a slightly greater than average proportion of buyers. This procedure is repeated for stocks in the sell-herding subgroup (ranked using $SHM_{i,t}$), giving another group of quintile portfolios. Here, the top portfolio (S1) contains stocks that funds most strongly sell in herds (that quarter), and the bottom portfolio (S5) contains stocks with only a slightly greater than average proportion of sellers.

Equal-weighted, size-adjusted, quarterly abnormal returns are calculated for each of these ten portfolios during the two quarters prior to the formation quarter, during the formation quarter, and during the following four quarters. To calculate these size-adjusted portfolio returns for a given quarter, we subtract, from the quarterly buy-and-hold return of each stock in the portfolio, the quarterly buy-and-hold return of the equal-weighted portfolio of all CRSP stocks belonging to the same size decile as that stock at the beginning of the quarter. Size breakpoints are based on NYSE stocks, and we update the breakpoints and the composition of the size control portfolios at the beginning of each quarter. Stocks included in the size control portfolios are those having a CRSP sharecode of 10, 11, or 12, which excludes closed-end funds, real estate investment trusts, primes and scores, American depository receipts, etc.

For all of the tests we present in the following tables, we also compute abnormal returns in an alternative way. For NYSE or AMEX stocks, we use size-control portfolios derived from the universe of NYSE and AMEX stocks (with NYSE size breakpoints); for Nasdaq stocks, we use size-control portfolios derived from the universe of Nasdaq stocks (with Nasdaq size breakpoints). We do not report the results of this alternative method, but they closely match the results that we present using nonsegregated size-control portfolios.

Table VI reports time-series average size-adjusted returns for portfolios B1 through S1, computed over all 80 event quarters from 1975 to 1994. For example, the return shown for portfolio B1 in the first quarter (quarter +1) represents the hypothetical size-adjusted quarterly return that would accrue to investing, on April 1, 1975, in an equal-weighted portfolio of stocks the funds most strongly buy as a herd during the first quarter of 1975, holding this portfolio until June 30, 1975, and then rebalancing to hold an equal-weighted portfolio of stocks that the funds most strongly buy as a herd

Table VI

Herding and Abnormal Stock Returns (1975–1994)

Each quarter, all stocks traded by at least five mutual funds and for which the proportion of funds trading the stock that buy it is higher than for the average stock during that quarter, is ranked by its buy-herding statistic ($BHM_{i,t}$). This herding statistic = $|p - E[p]| - E|p - E[p]|$ conditioned on $p > E[p]$, where the proxy for $E[p]$ is the proportion of all stock trades by mutual funds during the quarter that are purchases. $E|p - E[p]|$ conditioned on $p > E[p]$ is calculated under the null hypothesis of herding only by random chance. This sorting procedure is repeated for all stocks traded by at least five funds during the quarter and for which the proportion of trading funds that sell the stock is higher than average (that is, these stocks are ranked by $SHM_{i,t}$). Quintile portfolios are formed for the buy-herding sorted stocks and quintile portfolios are formed for the sell-herding sorted stocks, giving 10 portfolios. The quarterly abnormal return for each formation quarter decile portfolio is then calculated as the equally weighted quarterly buy-and-hold return of the stocks in that decile minus the equally weighted quarterly buy-and-hold return of a size control portfolio; that is, each stock in the decile portfolio is matched with an equally weighted portfolio of the CRSP stocks (excluding special issues, such as real estate investment trusts) in the same size decile (using NYSE breakpoints) as that stock at the beginning of the quarter. Finally, the time-series average quarterly abnormal return for each decile portfolio is computed across all 80 formation (event) quarters, and is presented below. "B1 minus S1" represents a zero-investment portfolio that is long the B1 portfolio and short the S1 portfolio. "B1 to B5 minus S1 to S5" equally weights long positions in B1 through B5 and equally weights short positions in S1 through S5 to create a zero-investment portfolio. Time-series t-statistics (in parentheses) are computed as the estimated mean (across all formation dates) divided by the estimated standard deviation of the mean.

	Average Herding-Sorted Equal-Weighted Portfolio Abnormal Returns (Quarterly, in percent)						
	Qtr −2	Qtr −1	Portfolio Formation Quarter	Qtr +1	Qtr +2	Qtr +3	Qtr +4
Portfolio B1	3.02***	4.22***	5.57***	0.90***	0.10	−0.05	−0.41*
(Heavy buying)	(9.16)	(10.40)	(13.11)	(3.14)	(0.32)	(−0.23)	(−1.94)
Portfolio B2	2.75***	2.67***	3.73***	0.66**	0.29	0.22	−0.25
	(9.87)	(9.03)	(11.48)	(2.63)	(1.28)	(1.10)	(−1.32)
Portfolio B3	1.95***	2.33***	2.28***	0.35*	−0.23	−0.04	−0.07
	(8.72)	(6.81)	(9.87)	(1.81)	(−1.22)	(−0.22)	(−0.31)
Portfolio B4	2.26***	1.54***	1.61***	0.42**	0.25	0.10	−0.04
	(7.84)	(8.06)	(6.72)	(2.07)	(1.28)	(0.56)	(−0.18)
Portfolio B5	1.48***	1.15***	0.78**	0.04	0.13	−0.04	−0.50**
(Light buying)	(6.48)	(5.31)	(3.80)	(0.18)	(0.64)	(−0.19)	(−2.59)
Portfolio S5	1.26***	0.89***	0.24	−0.11	−0.29	−0.46**	−0.22
(Light selling)	(4.33)	(3.85)	(1.24)	(−0.50)	(−1.47)	(−2.40)	(−1.11)
Portfolio S4	1.52***	1.10***	0.07	−0.22	−0.13	−0.26	−0.30
	(5.87)	(4.25)	(0.30)	(−1.11)	(−0.75)	(−1.16)	(−1.48)
Portfolio S3	1.36***	0.69**	−1.27***	−0.32	−0.36*	−0.65***	−0.20
	(5.35)	(2.61)	(−5.05)	(−1.50)	(−1.76)	(−3.43)	(−1.03)
Portfolio S2	1.03***	0.19	−1.97***	−0.52**	−0.21	−0.71***	−0.49**
	(3.41)	(0.62)	(−6.46)	(−2.11)	(−0.93)	(−2.99)	(−2.41)
Portfolio S1	0.11	0.40	−3.19***	−1.38***	−1.25***	−0.67**	−0.60*
(Heavy selling)	(0.27)	(0.92)	(−7.47)	(−4.07)	(−5.14)	(−2.09)	(−1.98)
B1 minus S1	2.92***	3.82***	8.76***	2.29***	1.35***	0.62	0.19
	(5.40)	(6.22)	(13.32)	(4.73)	(3.46)	(1.43)	(0.49)
B1 to B5	1.24***	1.73***	4.02***	0.98***	0.56***	0.59**	0.11
minus S1 to S5	(5.37)	(7.08)	(13.05)	(5.32)	(3.15)	(3.27)	(0.76)

*, **, *** Significant at the 90, 95, and 99 percent confidence levels, respectively.

during the second quarter of 1975. This process is repeated until the end of 1994; the average quarterly size-adjusted return is 0.9 percent. Similarly, the (insignificant) return of 0.1 percent shown for portfolio B1 in the second quarter (quarter +2) represents the average size-adjusted quarterly return that would accrue to waiting until July 1, 1975, to invest in an equal-weighted portfolio of stocks the funds most strongly buy during the first quarter of 1975, holding this portfolio until September 30, 1975, rebalancing, and so on.

The results, in general, show that abnormal stock returns are related to the direction of herding in stocks, especially during the portfolio-formation quarter. Somewhat surprising are the positive and significant average abnormal returns exhibited by most portfolios during the two quarters prior to the formation quarter; this indicates that funds tend to trade "winners" more often than "losers." This result is consistent with Lakonishok and Smidt (1986), who document that winners have a higher trading volume than losers. As we interpret further abnormal return patterns, the reader should keep in mind that the average stock (during the formation quarter) is a past winner.

Another finding shown in Table VI is that past returns are highest among stocks bought by herds and lowest among stocks sold by herds. Consistent with our previous results of Table IV, Panel B, herding (especially on the buy-side) is related to positive-feedback trading. As documented by Grinblatt et al. (1995), the majority of mutual funds tend to invest using a positive-feedback trading strategy (mainly buying winners); our results show that this results in funds purchasing many of the same past winners.

During the formation quarter, we find a similar relation between returns and the direction of trade. However, unlike the prior two quarters, stocks heavily sold by funds exhibit large and significantly negative returns. Because we must infer trades from end-of-quarter portfolio holdings of funds, we cannot determine whether the pattern of returns during the formation quarter is the result of positive-feedback trading by the funds or the result of an impact of fund trading on stock prices. Interesting to note, however, is that returns are much more highly related to the direction of herding during this quarter than during any other quarter; the difference in abnormal returns between portfolios B1 and S1 is nearly nine percent (see "B1 minus S1").

In a related paper, Sias and Starks (1997) find some evidence that institutional trading reflects information and increases the speed of daily stock price adjustments. We next analyze whether the same holds true for the impact of mutual fund trading on long-term returns. A temporary price adjustment would indicate that herding is destabilizing to stock prices; a permanent impact would indicate that herding plays a more beneficial role in stock markets by increasing the speed of price adjustment to new information.

Table VI shows that stocks heavily bought by funds outperform stocks heavily sold over the next six months. The return difference is biggest during the first quarter (quarter +1), with portfolio B1 outperforming S1 by more than two percent. Results for the second through fourth quarters (quarters +2 through +4) indicate that the return difference between portfolios B1 and S1 declines, but does not become negative. This permanent return effect is consistent with mutual fund herding speeding the price-adjustment process and not with herding being a destabilizing, temporary influence on stock prices. Results for equal-weighted portfolio B1 through B5 minus equal-weighted portfolio S1 through S5 are similar during these four quarters.

Finally, we note that stocks sold by herds exhibit a larger future return effect (in absolute value) than stocks bought by herds. This finding is consistent with our earlier results showing higher levels of herding, at least in trades of small stocks, on the sell-side. The finding is also troubling to those who may wish to capture abnormal profits by observing fund trades, as such a strategy would almost certainly require short-selling many small stocks.

We also note that, for the most part, average abnormal returns are small and insignificant during the third and fourth quarters. The large number of negative average returns during those quarters is most likely attributable to return reversals in stocks that are past winners (which comprise a majority of the stocks traded by mutual funds). In an earlier version of this paper, we looked at returns in the following year (quarters +5 through +8). For the most part, these results also show insignificant size-adjusted returns.

We might believe that larger herds would have a bigger impact on stock prices. For example, 16 out of 20 funds buying IBM would seem likely to result in a bigger price impact than four out of five buying IBM, but the two cases would have similar herding measures. To address this possibility, we repeat the tests performed in Table VI, this time including only stock-quarters traded by at least 20 funds. The unreported results are nearly the same: stocks heavily bought by funds outperform those heavily sold by approximately two percent during quarter +1. The pattern of returns in later quarters is also similar.

We repeat our tests in three other ways, all of which are mentioned in earlier sections in reference to computing herding measures. First, we exclude from the herding measure calculations (for a given stock-quarter) any trade by a fund with a dollar amount less than 0.1 percent of that fund's total net assets at the beginning of that quarter. This hurdle prevents minor portfolio adjustments from being labeled "herding." Second, we use a semi-annual measure of herding to accommodate the minority of funds that report holdings at that frequency. Third, we use a measure of herding where the fund management company (instead of an individual fund) is the unit of measurement. In all three cases (which are not reported), results are very similar to our baseline results of Table VI.

We also examine monthly (instead of quarterly) buy-and-hold size-adjusted returns for the first six months following the formation quarter. Again in unreported results, we find reasonably smooth returns across these months; abnormal returns are not conspicuously higher in any given month.

Finally, in an earlier version of this paper, we check the robustness of the abnormal return difference between stocks purchased and stocks sold by herds. We regress the excess return of each herding decile portfolio (the gross return minus T-bill return for portfolios B1 through S1 of Table VI) on the excess returns of the eight benchmark portfolios (the "P-8" benchmarks) developed in Grinblatt and Titman (1988) and used in Grinblatt and Titman (1989). The resulting alphas of these time-series regressions are roughly the same as our results using size-control portfolios.

C.2. The Impact of Herding on Small versus Large Stocks

One of the most striking results from Section B is the high level of herding (among growth funds) in small stocks. Here, we explore whether the impact of herding on small stock prices is different from that for large stocks. To achieve this, we repeat our tests of the last section: We rank stocks (traded by at least five funds) in a given quarter by their buy- or sell-herding measures ($BHM_{i,t}$ or $SHM_{i,t}$), then measure the size-adjusted returns of each resulting equal-weighted decile portfolio. However, we now rank only stocks in a given CRSP market capitalization quintile. As before, NYSE stocks are used to compute size-quintile breakpoints, which, along with size-quintile assignments, are updated at the beginning of each quarter. Because mutual funds trade small stocks relatively infrequently (see Table IV), we combine the smallest two quintiles to avoid forming very small portfolios when we rank on herding measures.

In Panel A of Table VII, we present hypothetical returns (based on the long position), by size quintile, for the zero-investment portfolio strategy that buys equal-weighted portfolio B1 and sells equal-weighted portfolio S1. Also presented (in the last row of Panel A) for comparison purposes are the results from Table VI.

We find a modest size-adjusted return for this buy-sell strategy in large stocks (Q-5), but the magnitude is much larger among small stocks. For the smallest two quintiles (Q-1 and Q-2), returns for the strategy average almost 13 percent during the formation quarter, followed by roughly four percent during each of the next two quarters. Also, returns during the two quarters prior to the formation quarter indicate that herding is very strongly related to positive-feedback trading in these stocks. In an unreported further analysis of these returns, we find that the majority of the return difference between portfolios B1 and S1 during quarters +1 and +2 results from the underperformance of stocks in portfolio S1, especially when looking at small stocks. A herd strongly selling a small stock is very bad news for the future performance of that stock.

By contrast, size-adjusted returns during quarters −2 and −1 are insignificant for the largest two quintiles of stocks (Q-4 and Q-5). Although results for these two quintiles during the formation quarter and the following quarter indicate a relation between the direction of herding and returns, this relation is much weaker than for small stocks. These results are similar to the Lakonishok et al. (1992) results for pension funds: Future stock returns are related to pension fund herding only for the three smallest size quintiles, which amount to about three percent of the total value of trades by pension funds. As documented in an earlier section, however, these smallest three quintiles are a much bigger part of mutual fund trading: they account for approximately 20 percent of the total value of all mutual fund trades.

Panel B presents analogous results for the zero-investment strategy that buys portfolios B1 through B5 in equal amounts, and sells S1 through S5. Returns presented in that panel show patterns similar to those of Panel A, although the magnitudes are smaller.

C.3. The Impact of Herding during Subperiods

We next split the sample period in half. Panel A of Table VIII presents size-adjusted returns (based on the long position) for the buy B1, sell S1 strategy, averaged over the ten-year period from 1975 to 1984. Panel B presents analogous results for the ten-year period from 1985 to 1994.

The return patterns during the formation quarter and the two prior quarters are not much different between the two sample periods. However, a sharp contrast may be drawn between the future quarter returns of the two periods. Mutual fund herding is much more highly related to future returns during the first ten-year period, among both small and large stocks. For example, small stocks (Q-1 and Q-2) bought by herds during the first ten-year period outperform those sold by herds by more than 13 percent during the following six months; for large stocks (Q-5) this difference is more than three percent. However, during the second ten-year period, herding is related to future returns only for small stocks—and even this relation is much weaker than during the first ten-year period. Thus, our previous results, which suggest an impact of mutual fund trading on future stock returns, are mainly driven by the first ten years of our sample.[22] Any impact of fund trading that might have been present in those early years appears to have become much less important in the later years.

C.4. Herding and Momentum in Stock Returns

In a prior version of this paper, we present results from two more tests. These tests are designed to determine the extent to which the future return difference between stocks bought and sold by herds can be explained by the use of positive-feedback strategies by the funds to capture momentum in stock returns. That is, do we still see a future return difference when herds buy versus sell stocks having similar past returns?

In the first test, we regress our first-quarter return difference time-series (B1 minus S1 of Table VI during quarter +1, rebalanced quarterly) on the four Carhart (1997) factor-mimicking portfolio return time-series; one of these

[22] This finding is consistent with recent studies that find higher levels of mutual fund performance during the first ten years (e.g., see Daniel et al. (1997)).

Table VII

Herding and Abnormal Stock Returns, by Size Quintile (1975–1994)

Each quarter, every stock traded by at least five mutual funds and for which the proportion of funds trading the stock that buy it is higher than for the average stock during that quarter, is ranked by its buy-herding statistic ($\mathrm{BHM}_{i,t}$). This sorting procedure is repeated for all stocks traded by at least five funds during the quarter and for which the proportion of trading funds that sell the stock is higher than average (that is, these stocks are ranked by $\mathrm{SHM}_{i,t}$). Quintile portfolios are formed for the buy-herding sorted stocks and quintile portfolios are formed for the sell-herding sorted stocks, giving 10 portfolios. The quarterly abnormal return for each formation quarter decile portfolio is then calculated as the equally weighted quarterly buy-and-hold return of the stocks in that decile minus the equally weighted quarterly buy-and-hold return of a size control portfolio; that is, each stock in the decile portfolio is matched with an equally weighted portfolio of the CRSP stocks (excluding special issues, such as real estate investment trusts) in the same size decile (using NYSE breakpoints) as that stock at the beginning of the quarter. Finally, the time-series average quarterly abnormal return for each decile portfolio is computed across all 80 formation (event) quarters. Panel A presents the mean (across all portfolio-formation dates, in event time) quarterly abnormal return to a zero-investment portfolio which is long the equal-weighted decile portfolio containing stocks that the mutual funds most strongly bought as a herd and short the decile portfolio containing stocks the funds most strongly sold as a herd. Results are presented for the sorting procedure separately implemented on different size quintiles, as well as for the sorting procedure implemented on all stocks. Panel B presents similar computed return differences, except these zero-investment portfolios are long the equal-weighted portfolio of all stocks with higher than average buying by the funds ("buy" stocks) and short all stocks with lower than average buying "sell" stocks. Time-series t-statistics (shown in parentheses) are computed as the estimated mean (across all portfolio formation dates) divided by the estimated standard deviation of the mean. The sorting procedure for the Q-1 and Q-2 portfolio begins with the second quarter of 1978 (portfolio formation quarter) due to very small portfolio sizes during earlier quarters. Note that the Q-1 through Q-5 category (all stocks) does not equal the average of the individual quintiles, since it is populated more heavily with small stocks than with large stocks.

	Qtr −2	Qtr −1	Portfolio Formation Quarter	Qtr +1	Qtr +2	Qtr +3	Qtr +4
Panel A: Top Buy-Herding Decile minus Top Sell-Herding Decile (B1 minus S1)							
Q-1 and Q-2	7.85***	9.33***	12.81***	4.21***	3.69***	0.35	−1.15
(Small stocks)	(8.75)	(7.58)	(10.86)	(4.11)	(3.58)	(0.31)	(−1.07)
Q-3	0.76	2.51**	7.43***	2.39***	0.98	1.48**	1.02
	(0.59)	(2.02)	(7.92)	(3.54)	(1.31)	(2.12)	(1.33)
Q-4	−0.66	0.59	6.19***	0.71	0.78	0.11	−0.26
	(−1.08)	(0.89)	(7.27)	(1.31)	(1.42)	(0.17)	(−0.53)
Q-5 (Large stocks)	−0.61	−0.26	4.78***	1.42***	0.55	0.63	0.73
	(−1.36)	(−0.42)	(7.11)	(2.84)	(1.33)	(1.06)	(1.36)
Q-1 through Q-5	2.92***	3.82***	8.76***	2.29***	1.35***	0.62	0.19
	(5.40)	(6.22)	(13.32)	(4.73)	(3.46)	(1.43)	(0.49)
Panel B: All Buy Stocks minus All Sell Stocks (B1 to B5 minus S1 to S5)							
Q-1 and Q-2	3.77***	4.61***	5.93***	2.14***	1.18***	0.61	−0.44
(Small stocks)	(9.34)	(10.63)	(10.87)	(5.32)	(2.82)	(1.36)	(−1.11)
Q-3	1.07***	1.86***	4.04***	1.11***	0.67**	0.93***	−0.04
	(3.77)	(4.58)	(7.69)	(3.78)	(2.21)	(3.23)	(−0.12)
Q-4	−0.23	0.35	2.99***	0.66***	0.45*	0.52**	−0.12
	(−0.80)	(1.36)	(8.57)	(2.89)	(1.89)	(2.28)	(−0.51)
Q-5 (Large stocks)	−0.26	−0.35	2.43***	0.25	0.27	0.38	0.35
	(−1.22)	(−1.46)	(8.34)	(1.18)	(1.29)	(1.55)	(1.41)
Q-1 through Q-5	1.24***	1.73***	4.02***	0.98***	0.56***	0.59***	0.11
	(5.37)	(7.08)	(13.05)	(5.32)	(3.15)	(3.27)	(0.76)

*, **, *** Significant at the 90, 95, and 99 percent confidence levels, respectively.

Table VIII

Herding and Abnormal Stock Returns, by Size Quintile (Over Subperiods)

Each quarter, every stock traded by at least five mutual funds and for which the proportion of funds trading the stock that buy it is higher than for the average stock during that quarter is ranked by its buy-herding statistic ($\mathrm{BHM}_{i,t}$). This sorting procedure is repeated for all stocks traded by at least five funds during the quarter and for which the proportion of trading funds that sell the stock is higher than average (that is, these stocks are ranked by $\mathrm{SHM}_{i,t}$). Quintile portfolios are formed for the buy-herding sorted stocks and quintile portfolios are formed for the sell-herding sorted stocks, giving ten portfolios. The quarterly abnormal return for each formation quarter decile portfolio is then calculated as the equally weighted quarterly buy-and-hold return of the stocks in that decile minus the equally weighted quarterly buy-and-hold return of a size control portfolio; that is, each stock in the decile portfolio is matched with an equally weighted portfolio of the CRSP stocks (excluding special issues, such as real estate investment trusts) in the same size decile (using NYSE breakpoints) as that stock at the beginning of the quarter. Finally, the time-series average quarterly abnormal return for each decile portfolio is computed across 40 formation (event) quarters in a 10-year subperiod. Panel A presents the mean (across all portfolio-formation dates from 1975–1984, in event time) quarterly abnormal return to a zero-investment portfolio which is long the decile portfolio containing stocks that the mutual funds most strongly bought as a herd and short the decile portfolio containing stocks the funds most strongly sold as a herd. Results are presented for the sorting procedure separately implemented on different size quintiles, as well as for the sorting procedure implemented on all stocks. Panel B presents similar computed return differences for the period 1985–1994. Time-series t-statistics (shown in parentheses) are computed as the estimated mean (across all portfolio formation dates) divided by the estimated standard deviation of the mean. The sorting procedure for the Q-1 and Q-2 portfolios begins with the second quarter of 1978 (portfolio formation quarter) due to very small portfolio sizes during earlier quarters. Note that the Q-1 through Q-5 category (all stocks) does not equal the average of the individual quintiles, since it is populated more heavily with small stocks than with large stocks.

	Qtr −2	Qtr −1	Portfolio Formation Quarter	Qtr +1	Qtr +2	Qtr +3	Qtr +4
Panel A: Top Buy-Herding Decile minus Top Sell-Herding Decile (B1 minus S1; 1975–1984)							
Q-1 and Q-2	6.31***	11.08***	10.39***	7.32***	5.97***	1.41	−1.35
(Small stocks)	(3.73)	(4.42)	(4.67)	(3.94)	(2.85)	(0.62)	(−0.60)
Q-3	−1.07	4.46**	8.54***	3.55***	2.34**	2.36*	2.38*
	(−0.44)	(2.12)	(6.08)	(3.26)	(2.00)	(1.94)	(1.99)
Q-4	−1.40	0.30	7.30***	1.01	1.20	0.53	0.31
	(−1.50)	(0.35)	(5.12)	(1.21)	(1.50)	(0.54)	(0.45)
Q-5 (Large stocks)	−1.51**	−0.67	5.34***	2.25***	1.23***	1.20	1.56*
	(−2.41)	(−0.84)	(5.40)	(3.22)	(2.73)	(1.56)	(1.96)
Q-1 through Q-5	0.64	2.94***	8.23***	3.22***	1.53***	1.00	1.08***
	(0.98)	(3.79)	(8.73)	(5.56)	(2.77)	(1.62)	(2.90)
Panel B: Top Buy-Herding Decile minus Top Sell-Herding Decile (B1 minus S1; 1985−1994)							
Q-1 and Q-2	8.88***	8.15***	14.45***	2.10*	2.15**	−0.37	−1.02
(Small stocks)	(9.25)	(6.95)	(11.64)	(1.98)	(2.30)	(−0.33)	(−1.03)
Q-3	2.60***	0.56	6.32***	1.22	−0.39	0.61	−0.35
	(2.99)	(0.44)	(5.11)	(1.60)	(−0.44)	(0.89)	(−0.38)
Q-4	0.07	0.87	5.08***	0.42	0.36	−0.30	−0.83
	(0.09)	(0.88)	(5.54)	(0.59)	(0.48)	(−0.35)	(−1.18)
Q-5 (Large stocks)	0.30	0.15	4.22***	0.59	−0.12	0.07	−0.09
	(0.49)	(0.16)	(4.62)	(0.84)	(−0.18)	(0.08)	(−0.13)
Q-1 through Q-5	5.19***	4.70***	9.28***	1.36*	1.16**	0.23	−0.70
	(7.41)	(5.00)	(10.09)	(1.80)	(2.10)	(0.39)	(−1.10)

*, **, *** Significant at the 90, 95, and 99 percent confidence levels, respectively.

return series captures the momentum premium. The resulting alpha from this regression is positive and significant, although it is only about one percent per quarter.

In our second test, we separate stocks having high past returns from those having low past returns. Then we measure the difference in future returns between stocks bought and sold by herds for each of these two past-return groups. In this test, we find slightly more compelling results than in the first test. For past winners, the difference in next quarter returns between stocks bought and sold by herds is about 1.8 percent; for past losers it is about 2.3 percent. However, the results are muddied by the fact that contemporaneous quarter returns also differ by a large amount, weakening the argument that we fully control for momentum. We, therefore, must end this section with a qualified conclusion: The direction of mutual fund herding appears to be related to future stock returns after controlling for momentum in stock prices, although we are not sure how strong this relation is.

III. Conclusion

This paper studies the tendency of mutual fund managers to herd in their trades of stocks from 1975 to 1994. Although we find an average level of herding similar to that found by a recent study of pension funds, we find much higher levels of herding in small stocks and in trading by growth-oriented mutual funds. We also find that herding by growth-oriented funds is related to positive-feedback trading strategies: Herding on the buy-side is strongest in high past-return stocks; herding on the sell-side is strongest in low past-return stocks. We find little evidence that sell-side herding is related to window-dressing strategies.

We also study the relation between mutual fund herding and both contemporaneous and future stock returns. We find that stocks bought by herds have, on average, contemporaneous and future returns that are higher than stocks sold by herds. The difference in contemporaneous returns is most striking, with an average size-adjusted return difference of almost nine percent between stocks most strongly bought and stocks most strongly sold by herds. Of course, given the quarterly nature of our holdings data, we cannot determine whether this return difference is mainly due to intraquarter feedback strategies or to an impact of herding on stock prices.

An examination of future returns is useful in light of the various theories of herding. We find that stocks strongly bought by herds outperform those strongly sold by herds during the following six months. This return difference is especially pronounced among small stocks, although we also find a modest return difference among large stocks. Future return differences appear to be permanent, suggesting that our empirical results are most consistent with theories where managers herd on new information about the future prospects of firms and help to speed the incorporation of this new information into prices.

Although the level of future abnormal returns suggests that mutual funds may together be choosing well-performing stocks, a substantial portion of these returns is related to the one-year momentum effect in stock returns. The potential problems with executing a positive-feedback strategy, as described by Chan et al. (1996), include large bid-ask spreads of small stocks and other costs of transacting in such a strategy. Indeed, we find that, by far, the largest hypothetical profits accrue to herding in small stocks, which have the largest proportionate trading costs. Moreover, short-selling small stock portfolios, an investment strategy not available to most mutual funds, would be required to capture the majority of these returns. We thus conclude that herding by mutual funds appears to be profitable before, but perhaps not after, expenses.

Appendix A. CDA Database and Data-Collection Procedures

In this appendix, we describe the structure of the mutual fund holdings database, and the collection procedure used by CDA Investment Technologies, Inc., of Rockville, Maryland, in building this database. The first ten years of data, which include mutual fund data beginning December 31, 1974, and ending December 31, 1984, (inclusive) were purchased during 1985. The second ten years of data, which include the range January 1, 1985, to December 31, 1994, (inclusive) were purchased during 1995. We believe that the completeness and accuracy of the two databases are very similar, although it is likely that slightly more errors and omissions exist for the first few years CDA collected such data (e.g., 1975 and 1976) and for the last few years (e.g., 1993 and 1994). The first years were a startup period for the data collection, and in the last years the huge expansion in the number of funds made data collection more difficult. However, CDA attempts to find and correct errors in past data; remaining errors are mainly associated with very small funds. From the client's point of view, this error-correction procedure ends only when the database is finally delivered.

The database provides the following information for virtually all U.S.-based mutual funds (that invest at least part of their portfolios in equities), along with a number of foreign-based funds (mainly Canadian) at the end of each calendar quarter during the 20-year period:

1. fund name and fund management company name
2. date of most recent mutual fund holdings "snapshot" (since June 30, 1979; see discussion below)
3. total net assets
4. self-declared investment objective (since June 30, 1980)
5. number of shares held of each stock by each fund at the most recent holdings snapshot.

The main source of these data are reports filed by the funds with the SEC. Prior to 1985, Section 30 of the Investment Company Act of 1940 required individual funds to report portfolio holdings at the end of each fiscal quarter. Beginning in 1985, the SEC required individual mutual funds to file the report only twice per year. These semiannual reporting dates are determined by the fiscal year chosen by a given mutual fund, (one fund might choose a semiannual cycle of February to August, another might choose June to December) with the filing required within 60 days after the end of each fiscal six-month period.

Another source of data is voluntary reports by the mutual funds, whether they are quarterly reports normally provided to fund shareholders or informal reports made only to CDA. On an ongoing basis, CDA maintains and updates a database of fund names, and the company formally requests to subscribe to any such holdings reports from each fund that is listed in its "names database." The names database is compiled from several sources, including *The Wall Street Journal*.

CDA makes an effort to ensure that its holdings database is as complete as possible; the company uses its names database to contact fund companies that are delinquent in sending quarterly information, if the company normally sends information at that frequency. Reports not required by the SEC are generally available within 60 to 90 days after the end of a calendar quarter. This procedure allows CDA to update holdings quarterly for the majority of domestic funds (the proportion of foreign funds that is updated quarterly is much smaller).

No matter what the source of data, CDA provides an estimate of quarterly holdings for every fund. For those funds not filing every quarter, CDA fills in "missing quarters" by carrying forward the holdings of the prior quarter. CDA makes appropriate adjustments for CUSIP changes, stock splits, and other stock distributions to any such holdings that are carried forward from prior quarters to maintain a passive "no-trade" strategy during the carry-forward period.

Beginning on June 30, 1979, CDA documents the date of the portfolio holdings "snapshot" from which a given quarter's data are derived. For example, if a particular fund did not supply a quarterly report for its fiscal quarter ending on June 30, 1985, then CDA carries forward the holdings (and other data) from the fund's March 31, 1985 quarterly report (with appropriate adjustments), assuming that the March 31 quarterly report is available (if not, the most recent portfolio snapshot data are carried forward). CDA then enters the date "March 31, 1985" as the holdings date from which the June 30 data are derived. This snapshot date reporting by CDA is also useful to determine the number of funds using a fiscal quarter that does not coincide with calendar quarters. For example, a fund that provides a portfolio snapshot for May 31, 1985, is recorded as such, even though its holdings (with appropriate adjustments) are included with funds that report on June 30, 1985. The vast majority of mutual funds use a fiscal quarter that coincides with calendar quarters; therefore, for this study, we use the approximation that all holdings reported within a given calendar quarter are also valid for the end of that calendar quarter (with appropriate adjustments).

Although CDA believes that it tracks virtually all publicly offered U.S.-based mutual funds in existence during each quarter, it is possible that some small biases may be inherent in the database. For example, CDA states that holdings information for very small funds is the most difficult to obtain, so most missing funds are very small funds. However, we do not believe that such biases materially affect this study.

Appendix B. Description of Monte Carlo Simulation Procedure

In this appendix, we describe the procedure used to generate a simulated distribution of herding measures ($HM^*_{i,t}$) corresponding to the actual herding measures ($HM_{i,t}$) for our sample of stock-quarters traded by the mutual funds. Under the null hypothesis of herding only by random chance, each mutual fund makes its trading decision for each stock-quarter independently of the trading decisions of all other funds. The number of mutual funds that buy stock-quarter i,t is modeled as a binomial distribution, $b(n_{i,t},p_t)$, where $n_{i,t}$ is the number of funds actually trading stock-quarter i,t, and p_t is the proportion of funds in the population that, should they trade stock-quarter i,t, would be buyers (under the null hypothesis). As described in Section I.B, we use the actual proportion of trades of all stocks during quarter t that are buys as a proxy for p_t.

For a given stock-quarter, the simulation proceeds as follows. First, a random-number generator is used to produce a draw from a $U(0,1)$ distribution (uniformly distributed between zero and one). If the random draw is less than $1 - p_t$, the outcome is rounded to zero, otherwise, it is rounded to one, giving a draw from a Bernoulli distribution with parameter p_t. This procedure is repeated, giving a sample of $n_{i,t}$ Bernoulli draws, whose outcomes are summed to give a draw from a binomial distribution, $b(n_{i,t},p_t)$. This binomial draw represents the number of purchases randomly occurring among $n_{i,t}$ purchases and sales of stock i during quarter t. Then, $p^*_{i,t}$, the resulting simulated proportion of funds buying stock-quarter i,t, is calculated by dividing the simulated number of purchases by $n_{i,t}$. Finally, the simulated draw from the distribution of herding measures for stock-quarter i,t (under the null hypothesis) is computed from the equation,

$$HM^*_{i,t} = |p^*_{i,t} - E[p^*_{i,t}]| - E|p^*_{i,t} - E[p^*_{i,t}]|, \tag{B1}$$

after computing $E|p^*_{i,t} - E[p^*_{i,t}]|$, which is easily calculated by again using the assumption that the number of purchases is binomially distributed. This procedure is repeated to give a total of 10 simulated herding-measure outcomes for each stock-quarter actually traded by the funds.

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