Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior

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This study analyzes the extent to which mutual funds purchase stocks based on their past returns as well as their tendency to exhibit "herding" behavior (i.e., buying and selling the same stocks at the same time). We find that 77 percent of the mutual funds were "momentum investors," buying stocks that were past winners; however, most did not systematically sell past losers. On average, funds that invested on momentum realized significantly better performance than other funds. We also find relatively weak evidence that funds tended to buy and sell the same stocks at the same time. (*JEL* G14, G23)

The amount of wealth managed by institutional investors has grown considerably over the past 20 years. Due perhaps to decreased trading costs, brought about by the termination of fixed commissions in May 1975, these institutional investors have become much more active traders and, as a result, have become increasingly important in terms of setting market prices.[1] The growing influence of institutional investors has led to increased scrutiny both by policymakers and by journalists, who tend to believe that these investors trade excessively and move in and out of stocks in a herd-like manner. This tendency to invest with the herd, in combination with the alleged tendency of institutions to follow momentum-based fads by buying past winners and selling past losers is of concern, since this behavior could potentially exacerbate stock-price volatility.

Momentum trading strategies and herding behavior are also used by academics to motivate models of seemingly irrational markets. Fischer Black (1986) and Brett Trueman (1988) provide reasons why institutional investors may trade excessively, and a number of recent theory papers provide rationales to explain why institutional investors would analyze the same groups of stocks and trade in the same direction.[2] In addition, J. Bradford De Long et al. (1990) describe what they call "positive-feedback traders," who have a tendency to buy stocks after they perform well.

Our study provides empirical evidence on the trading patterns of fund managers by examining the quarterly holdings of 155 mutual funds over the 1975–1984 period. We char-

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[1] Institutional holdings are now about 50 percent of total equity holdings in the United States, while institutional trading, when added to member trading, accounted for about 70 percent of total NYSE volume in 1989 (Robert Schwartz and James Shapiro, 1992).

[2] These papers include Robert J. Shiller and John Pound (1989), Michael Brennan (1990), David S. Scharfstein and Jeremy C. Stein (1990), Josef Lakonishok et al. (1991), Abhijit Banerjee (1992), Sushil Bikhchandani et al. (1992), Kenneth A. Froot et al. (1992), and David Hirshleifer et al. (1994).

acterize the portfolio choices of these funds to determine the extent to which they purchase stocks based on their past returns and the extent to which they "herd," that is, the extent to which the group either predominantly buys or predominantly sells the same stock at the same time. We then examine the extent to which herding and momentum investing affect the performance of the funds.[3] If either irrationality or agency problems generate these trading styles (as discussed, for example, by Scharfstein and Stein [1990]), then mutual funds that exhibit these behaviors will tend to push the prices of stocks that they purchase above intrinsic values, thereby realizing lower future performance. However, if this type of behavior arises because informed portfolio managers tend to pick the same underpriced stocks, then funds that exhibit these styles should realize high future performance.

Our analysis of momentum investing and performance is also motivated by two previous studies (Grinblatt and Titman, 1989a, 1993), which indicate that, at least before transaction costs, a number of mutual funds earned significant risk-adjusted abnormal returns. This observed performance is not related to known anomalies that involve cross-sectional differences in expected returns, like the small-firm effect. However, before we conclude that these abnormal returns are generated by either superior information or analysis, we would also like to rule out the possibility that the observed abnormal performance was generated by exploiting time-series anomalies. Specifically, we would like to determine the extent to which the observed performance was generated by the simple momentum strategy of buying past winners and selling past losers, as described in Narasimhan Jegadeesh and Titman (1993). This simple strategy would generate abnormal performance with either of the Grinblatt and Titman (1989a, 1993) performance measures, as well as with any of the more traditional measures.

The paper is organized as follows. Section I describes the data, while Section II describes the methodology used to compute the degree of momentum (or contrarian) investing behavior exhibited by a fund. Section III presents empirical results on momentum investment styles and performance. Section IV investigates the tendency of the funds to engage in herding behavior and also considers the relation of herding behavior to momentum investing and performance. Finally, Section V summarizes and concludes the paper.

I. Data

Quarterly portfolio holdings for 274 mutual funds that existed on December 31, 1974, were purchased from CDA Investment Technologies, Inc. of Silver Springs, Maryland. These mutual fund data, used previously by Grinblatt and Titman (1989a, 1993) to examine fund performance, include 155 funds that existed during the entire 10-year time period of December 31, 1974, to December 31, 1984.[4] Center for Research in Security Prices (CRSP) monthly returns for each NYSE- and AMEX-listed stock held by the funds were computed by compounding returns in the CRSP daily returns file. Over-the-counter (OTC) stocks and fixed-income holdings were treated as missing values in a manner that we will describe shortly.

[3] Irwin Friend et al. (1970) were perhaps the first to examine the trading patterns of mutual funds. They found, among other things, that there was a tendency of some mutual funds to follow the prior investment choices of their more successful counterparts. Alan Kraus and Hans R. Stoll (1972) examined the tendency of mutual funds and bank trusts to buy and sell the same stocks at the same time but did not find evidence of herding beyond that due to chance. Lakonishok et al. (1992) examined the amount of herding exhibited by pension fund managers. They found only weak evidence of the funds either buying or selling in herds (above chance occurrences) and a weak relation between herding in stocks and the past returns of the stocks.

[4] The analysis in Grinblatt and Titman (1989a) and Stephen J. Brown and William N. Goetzmann (1995) indicates that this fund-survival requirement has only a small effect on inference tests of performance abilities. In our later analysis of the herding of funds into individual stocks, we expand our sample to include all 274 funds, which includes nonsurvivors.

II. Methodology

A. *The Momentum Measures*

A momentum investor buys past "winners" and sells past "losers." A contrarian investor does the opposite. Our measure of momentum investing is

$$M = \frac{1}{T} \sum_{t=1}^{T} \sum_{j=1}^{N} (\tilde{w}_{j,t} - \tilde{w}_{j,t-1}) \tilde{R}_{j,t-k+1} \tag{1}$$

where $\tilde{w}_{j,t}$ is the portfolio weight on security j at date t, and $\tilde{R}_{j,t-k+1}$ is the return of security j ($j = 1, \ldots, N$) from date $t - k$ to date $t - k + 1$, the historical benchmark period.

This statistic is designed to measure the degree to which a fund manager tilts his portfolio in the direction of stocks that have experienced high returns in some historical benchmark period, and away from stocks that have experienced low returns. Since this measure equals the difference between two portfolio returns during the benchmark period, a positive measure means that, on average, the fund's current portfolio had higher returns than the portfolio that the fund would have held had no portfolio revisions been made.

Since the mutual fund holdings are only available quarterly, while stock returns are available monthly, further modifications of the measure given by equation (1) are needed to arrive at the measures of momentum that are implemented. Given that we have 41 quarters of holdings, with three monthly returns per quarter, equation (1) is modified as follows:[5]

$$M = \frac{1}{120} \sum_{t=1}^{40} \sum_{i=1}^{3} \sum_{j=1}^{N} (\tilde{w}_{j,3t} - \tilde{w}_{j,3t-3}) \tilde{R}_{j,3t-3k+i}. \tag{2}$$

Since the most recent returns are probably of the greatest interest to portfolio managers, $k = 1$ and $k = 2$ are the two measures that we will focus on, although we will present some results for $k > 2$. We will refer to equation (2) as "lag-0 momentum" (L0M) when $k = 1$, and as "lag-1 momentum" (L1M) when $k = 2$.

B. *Statistical Inference*

As described by equation (2), the differenced portfolio weights were updated every calendar quarter, while the differenced portfolio return was generated each month.[6] This process resulted in a time series of 120 monthly return differences for each mutual fund. If the return differences associated with these measures are serially uncorrelated under the null hypothesis of no momentum investing, then inference-testing for the significance of the measures is simple. Testing whether the momentum measure has a mean value of zero is identical to a test of whether two given portfolios (with dynamic weight vectors) have the same mean return.[7]

We employ many cross-sectional regressions in our analysis, mainly of fund performance on fund characteristics. Statistical significance cannot be inferred from the cross-sectional t and F statistics typically reported in such regressions, since the regression residuals are correlated across mutual funds. Thus, we use alternative t and F tests that are derived from a time-series procedure (see Grinblatt and Titman, 1994).

[5] Using monthly returns rather than quarterly returns reduces the problem of missing returns. For example, if returns for the Boeing Corporation common stock are available from the CRSP for January and February, but not March, then Boeing drops out of our momentum investing measure in only one observation out of 120 (using monthly returns), instead of one out of 40 (using quarterly returns). See also footnote 6.

[6] The differenced weights are identical for any three months in the same calendar quarter, except when return data are not available for one or more securities in some (but not all) of the three months. For example, if returns for the Boeing Corporation are available in January and February, but not in March, then the differenced portfolio weight of Boeing is set to zero only for March, and it is identical for January and February.

[7] Since most portfolios of interest, such as value-weighted portfolios, have changing weights, the ordinary t tests that are usually applied in these tests are technically inappropriate. However, if securities returns are serially uncorrelated, the central-limit theorem can be applied and asymptotic z tests and chi-square tests are valid for nonnormal portfolio returns. Given the length of our time series, these asymptotic test statistics are virtually identical to the t and F statistics used here and have negligibly different significance levels.

C. *Modifying the Measures to Eliminate ''Passive Momentum Investing''*

The portfolio weights of winning (losing) stocks increase (decrease) even if the number of shares held stays constant. In this case, the lag-0 momentum measure would indicate momentum investing for buy-and-hold investment strategies. To correct this, we calculate the weights using the average of the beginning- and end-of-quarter share prices.[8] For consistency, we make the same modification for all momentum measures, even though passive momentum investing affects only the lag-0 momentum measure.[9]

D. *Extensions of the Measure*

We will also use decomposed versions of the L0M measure, called ''Buy L0M'' and ''Sell L0M.'' A high Buy (Sell) L0M measure for a fund means that it bought winners (sold losers) strongly, on average. These two measures are the decomposition of equation (2) into partial sums:

(3a) Buy L0M

$$= \frac{1}{120} \sum_{t=1}^{40} \sum_{i=1}^{3} \sum_{\tilde{w}_{j,3t} > \tilde{w}_{j,3t-3}} (\tilde{w}_{j,3t} - \tilde{w}_{j,3t-3})(\tilde{R}_{j,3t-3+i} - \bar{R}_j)$$

(3b) Sell L0M

$$= \frac{1}{120} \sum_{t=1}^{40} \sum_{i=1}^{3} \sum_{\tilde{w}_{j,3t} < \tilde{w}_{j,3t-3}} (\tilde{w}_{j,3t} - \tilde{w}_{j,3t-3})(\tilde{R}_{j,3t-3+i} - \bar{R}_j).$$

[8] If the beginning-of-quarter price was not available for a given security in a given quarter, the end-of-quarter price was used, and vice versa.

[9] Because each fund's stock holdings are observed only quarterly in our data set, it is tempting to think that L0M may spuriously be nonzero because of fund performance. It is true that when the fund manager can achieve superior returns, the actual portfolio weights are correlated with future returns. However, since L0M uses *differenced* portfolio weights, a bias only arises when the portfolio revisions are predominantly at the beginning of the quarter (spuriously indicating momentum investing) or at the end of the quarter (spuriously indicating contrarian investment behavior). Since there is no a priori reason to believe that portfolio revisions that occur for the purpose of achieving superior performance should occur closer to the beginning of a quarter than to its end, we do not believe that a bias exists.

Here, we subtract means from returns in order to have measures that asymptotically approach zero under the null hypothesis of no momentum investing. The monthly return from 12 months ahead for security j is used as a proxy for $\bar{R}_j$.[10] We also use a similar decomposition of L1M into ''Buy L1M'' and ''Sell L1M.''

While the L0M and L1M statistics are appropriate measures of the extent to which past returns affect the total holdings of a fund, we also use a turnover-adjusted L0M (TAL0M) which measures the extent to which past returns affect portfolio trades, independent of the number of trades made by a fund during a time period. This measure is given by

(4) TAL0M

$$= \frac{1}{120} \sum_{t=1}^{40} \sum_{i=1}^{3} \frac{\sum_{j=1}^{N} (\tilde{w}_{j,3t} - \tilde{w}_{j,3t-3}) \tilde{R}_{j,3t-3+i}}{\sum_{\tilde{w}_{j,3t} > \tilde{w}_{j,3t-3}} (\tilde{w}_{j,3t} - \tilde{w}_{j,3t-3})}.$$

The turnover-adjusted measure (TAL0M) is the L0M measure, normalized so that the changes in weights of the stocks purchased (and the changes in weights of the stocks sold) sum to 1 during each quarter. The results give a more accurate picture of the average difference in past returns between stocks purchased and stocks sold across all quarters by a mutual fund, since a constant \$1 is invested and shorted each quarter. A mutual fund that trades very little, but buys past extreme winners and sells past extreme losers, will have a very high TAL0M measure, even though the unmodified L0M measure will be relatively small. Analogous to Buy L0M and Sell L0M, ''Buy TAL0M'' and ''Sell TAL0M'' decompose TAL0M into terms having $\tilde{w}_{j,3t} > \tilde{w}_{j,3t-3}$ and $\tilde{w}_{j,3t} < \tilde{w}_{j,3t-3}$, respectively.

[10] Admittedly, this is a noisy proxy for the expected return, but since there are large numbers of stocks and time periods averaged in the measures we report, the noisiness of the proxy has a negligible effect on our results.

TABLE 1—MOMENTUM-INVESTING SUMMARY STATISTICS FOR SAMPLE OF 155 MUTUAL FUNDS (QUARTERLY FUND PORTFOLIO HOLDINGS ARE FOR THE PERIOD DECEMBER 31, 1974, THROUGH DECEMBER 31, 1984)

Statistic	Total sample (N = 155)	Aggressive-growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
L0M (percent/quarter)	0.74	1.25	0.29	0.89	0.32	0.17	−0.05	0.95
t statistic	10.96**	9.80**	3.83**	10.71**	6.33**	1.63	−0.33	3.17**
Percentage positive	76.8	88.9	60.0	81.8	67.6	61.5	66.7	66.7
Wilcoxon probability	0.0001	0.0001	0.44	0.0001	0.01	0.30	0.64	0.64

$F1$-statistic (L0M in every category = 0): F = 51.57**
$F2$ statistic (L0M is equal across categories: F = 18.24**

Statistic	Total sample (N = 155)	Aggressive-growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
Buy L0M (percent/quarter)	1.03	1.53	0.50	1.07	0.64	0.69	0.28	1.70
t statistic	2.63**	2.90**	1.76†	2.65**	2.14*	2.08*	1.56	2.77**
Percentage positive	55.8	58.3	52.5	55.8	54.2	48.3	45.0	57.5
Wilcoxon probability	0.10	0.02	0.47	0.10	0.23	0.63	0.15	0.03

$F1$ statistic (Buy L0M in every category = 0): F = 5.85**
$F2$ statistic (Buy L0M is equal across categories): F = 0.04

Statistic	Total sample (N = 155)	Aggressive-growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
Sell L0M (percent/quarter)	−0.29	−0.40	−0.12	−0.13	−0.31	−0.51	−0.06	−0.60
t statistic	−0.86	−0.88	−0.55	−0.37	−1.18	−1.65†	−0.60	−1.16
Percentage positive	50.8	50.0	50.0	50.8	50.8	48.3	57.5	46.7
Wilcoxon probability	0.81	1.00	1.00	0.81	0.81	0.63	0.01	0.34

$F1$ statistic (Sell L0M in every category = 0): F = 0.62
$F2$ statistic (Sell L0M is equal across categories): F = 0.02

Statistic	Total sample (N = 155)	Aggressive-growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
L1M (percent/quarter)	0.30	0.53	−0.02	0.43	−0.04	0.03	0.40	1.08
t statistic	5.46**	4.18**	−0.33	6.16**	−1.01	0.36	2.18*	4.01**
Percentage positive	58.7	68.9	40.0	75.0	35.1	46.2	66.7	66.7
Wilcoxon probability	0.005	0.001	0.44	0.0001	0.02	0.74	0.64	0.64

$F1$ statistic (L1M in every category = 0): F = 12.16**
$F2$ statistic (L1M is equal across categories): F = 8.41**

Statistic	Total sample (N = 155)	Aggressive-growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
Buy L1M (percent/quarter)	0.85	1.34	0.32	0.83	0.45	0.56	0.38	1.99
t statistic	2.23*	2.72**	1.13	2.07*	1.50	2.01*	0.80	3.34**
Percentage positive	57.5	58.3	49.2	55.8	50.8	50.0	45.8	60.0
Wilcoxon probability	0.03	0.02	0.81	0.10	0.81	1.00	0.23	0.004

$F1$ statistic (Buy L1M in every category = 0): F = 3.36**
$F2$ statistic (Buy L1M is equal across categories): F = 0.06

Statistic	Total sample (N = 155)	Aggressive-growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
Sell L1M (percent/quarter)	−0.44	−0.72	−0.23	−0.28	−0.37	−0.41	0.05	−0.73
t statistic	−1.56	−1.78†	−1.27	−0.97	−1.75†	−1.77†	0.37	−1.60
Percentage positive	47.5	44.2	46.7	50.0	49.2	48.3	50.0	47.5
Wilcoxon probability	0.47	0.10	0.34	0.99	0.81	0.63	0.47	0.47

$F1$ statistic (Sell L1M in every category = 0): F = 1.91†
$F2$ statistic (Sell L1M is equal across categories): F = 0.06

Statistic	Total sample (N = 155)	Aggressive-growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
TAL0M (percent/quarter)	2.07	3.39	0.60	2.98	0.54	0.14	0.45	2.50
t statistic	9.50**	9.75**	1.16	9.27**	1.71†	0.36	0.37	2.42*
Percent positive	72.3	82.2	50.0	77.3	56.8	76.9	100.0	66.7
Wilcoxon probability	0.0001	0.0001	0.97	0.0001	0.29	0.01	0.06	0.64

$F1$ statistic (TAL0M in every category = 0): F = 30.39**
$F2$ statistic (TAL0M is equal across categories): F = 9.30**

TABLE 1—*Continued.*

Statistic	Total sample (N = 155)	Aggressive-growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
Buy TALOM (percent/quarter)	2.31	3.64	1.29	2.78	0.98	0.93	0.02	3.35
t statistic	1.93[†]	2.56*	1.32	2.18*	0.89	0.96	0.02	1.95[†]
Percentage positive	51.7	56.7	49.2	52.5	52.5	46.7	44.2	58.3
Wilcoxon probability	0.63	0.06	0.81	0.47	0.47	0.34	0.10	0.02

$F1$ statistic (Buy TALOM in every category = 0): F = 2.48*
$F2$ statistic (Buy TALOM is equal across categories): F = 0.06

Notes: The LOM statistic is the measure of momentum investing based on stock returns in the same quarter as the portfolio revisions. The L1M statistic is the measure of momentum investing based on stock returns in the quarter before the portfolio revisions. "TALOM" is the LOM statistic, with portfolio revisions normalized so that $1 of stocks are bought each quarter and $1 are sold. For each category above, an equally weighted portfolio of all funds in that category is formed. Then, the appropriate momentum-investing statistic is calculated for that mean portfolio for each month. Finally, the time-series mean and t statistic are calculated for that portfolio across all 120 months. Wilcoxon probability is the probability that the absolute value of the Wilcoxon-Mann-Whitney rank z statistic is greater than the absolute value of the observed z statistic, under the null hypothesis.

[†] Statistically significant at the 10-percent level.
* Statistically significant at the 5-percent level.
** Statistically significant at the 1-percent level.

III. Results

A. *Summary Data on the Degree of Momentum Investing*

Table 1 presents the average LOM measure for the entire sample, as well as for various investment-objective categories.[11] According to this table, about 77 percent of the mutual funds, 119 out of 155, buy "winners" and/or sell "losers," as defined by the LOM measure. The average LOM measure for all 155 funds over the 10-year period is 0.74 percent per quarter, indicating that, on average, the stocks held by a fund at the end of a given quarter had returns 0.74-percent higher, during that quarter, than the stocks held at the end of the previous quarter, which was highly statistically significant.[12] F tests strongly reject both that the average LOM is equal across investment-objective categories and that it is zero across categories. In unreported results, we also find that funds with the greatest tendency to buy winners in the first five years of the sample period are more prone to buy winners in the second five years of the sample period, indicating that some managers follow consistent "styles."

Table 1 also provides the average Buy LOM and Sell LOM measures for each category. Note that the results for the Buy LOM measure are largely similar to the LOM

[11] The mutual funds in this study were subdivided into seven investment-objective categories, according to their stated objectives. Aggressive-growth and growth funds invest in the common stock of growth companies, with the primary aim of achieving capital gains instead of dividend income. Growth-income funds seek to provide both capital gains and a steady stream of income by buying the shares of high-yielding conservative stocks. Balanced funds invest in both stocks and bonds, intending to provide capital gains and income while preserving principal. Income funds seek to provide high current income by buying government and corporate bonds as well as high-yielding common and preferred stock. Finally, special-purpose and venture-capital/special-situations funds, as their names suggest, have very specialized strategies that vary from fund to fund. These two categories represent a very small portion of our sample.

[12] Nonparametric test results, designated by Wilcoxon probabilities, generally agree with the standard t statistics.

results. For example, the aggressive-growth, growth, and growth–income categories have the highest average L0M measures among the five investment-objective categories with nonnegligible numbers of funds, while the aggressive-growth, growth, and income categories have the highest Buy L0M measures. Note, however, that the Sell L0M measures are insignificant (at the 5-percent level) for every category, and a joint test of significance cannot reject that the seven average Sell L0M measures are all equal to zero. Therefore, momentum investing appears to be almost entirely driven by funds buying winners, and not by selling losers.

The results for L1M, Buy L1M, and Sell L1M are much the same. The L1M measure is significantly positive, on average, indicating that fund managers had a tendency to select stocks based on superior returns over the prior quarter. The average one-quarter-lagged momentum measure is about 0.30 percent per quarter, suggesting that, on average, the most recent quarter's returns were more important determinants of portfolio choice (as shown by L0M) than the returns realized in the more distant past (as shown by L1M). In unreported regressions, we found a strongly positive cross-sectional correlation between the L0M and L1M measures of the funds. The regression of L1M on L0M gave a coefficient of 0.48, with a time-series t statistic of 5.5; the reverse regression of L0M on L1M gave a coefficient of 0.88, with a time-series t statistic of 10.0).[13] As with the L0M measure, the aggressive-growth and growth categories had, on average, the highest levels of L1M-measured momentum investing, which is due, in part, to a larger percentage of these funds trading on momentum, relative to other funds (about 89 percent and 82 percent of aggressive-growth and growth funds, respectively, followed momentum strategies, according to their L0M measures).

Despite its statistical significance, the 0.74-percent (0.30-percent) quarterly return for the L0M (L1M) measure seems economically insignificant. The results for the turnover-adjusted measures, TAL0M and Buy TAL0M (also shown in Table 1), provide a more dramatic confirmation of the momentum investing behavior of the funds. For both measures, the average difference between buy and sell portfolios across all 155 funds was about 2 percent per quarter, confirming that buying winners is the chief method of momentum investment. In unreported results, we found that the top 10 funds, ranked by TAL0M, bought portfolios of stocks with returns that were more than 8 percent (quarterly) greater than the portfolios of stocks they sold, on average; the top 25 had a difference of about 6 percent.

The TAL0M results in Table 1 also confirm that the aggressive-growth and growth funds were much more likely to have traded on momentum than funds in other large categories: their larger L0M measures were not primarily due to higher turnover than other categories (since TAL0M is adjusted for turnover). Again, results from nonparametric tests generally agree with the standard t-statistic results.

In results not reported in Table 1, we also computed Buy L0M measures for partitions of stocks in the portfolio based on the market capitalization of the stocks, in order to measure the relative contribution of buying winners in different size deciles to the overall L0M measure. For all objective categories, and for the total sample of funds, buying large-capitalization past winners provided almost all of the contribution to the observed momentum-investing behavior. We also found no significant evidence of selling past losers in any size decile.

B. *The Relation between Momentum Investing and Superior Portfolio Performance*

In this subsection, we examine the extent to which a fund's tendency to hold past winners relates to its performance. As mentioned earlier, past research (Jegadeesh and Titman, 1993) suggests that stocks that perform relatively well over a 3–6-month period tend to realize relatively good performance during the next year. Hence, mutual funds that hold stocks that performed well in the recent past

[13] These two regressions imply a correlation of 0.65 between L0M and L1M.

should realize better performance than those funds that hold stocks that did not perform well.

In order to measure mutual fund performance, we employ the method developed by Grinblatt and Titman (1993), which does not require that we select a benchmark portfolio. The performance measure (α) developed in that paper uses a four-quarter change in (unmodified) portfolio weights and multiplies the differenced weights by a future return; that is,

$$(5) \qquad \alpha = \frac{1}{111} \sum_{t=1}^{37} \sum_{i=1}^{3} \sum_{j=1}^{N} (\tilde{w}_{j,3t+9} - \tilde{w}_{j,3t-3}) \tilde{R}_{j,3t+9+i}.$$

With this measure, the benchmark used to adjust the return of a portfolio for its risk in a given month is the current month's return earned by the portfolio holdings four quarters prior to the current quarter's holdings. Therefore, α represents the mean return of a zero-investment portfolio.[14] If the systematic risks of the current and benchmark portfolios are the same from the point of view of an investor with no selectivity or timing abilities (as defined by Grinblatt and Titman [1989b]), the performance represented by α should be insignificant for that investor.[15]

We first split our sample of 155 funds into momentum and contrarian investors, based on the sign of L0M and L1M, and examined the performance of these two subgroups. Table 2A compiles mean L0M measures for the total sample and for the five largest investment-objective categories. For the sample of all 155 funds, the 119 funds using momentum investment strategies clearly outperformed the 36 funds using contrarian strategies over the ten-year period. The performance of the momentum investors averaged about 2.6 percent per year, while the contrarians had an insignificant average performance of about 0.1 percent per year. Similar results held for most of the individual investment-objective categories.

Table 2B repeats this analysis with L1M as the momentum investing measure. The 91 L1M momentum investors outperformed the 64 L1M contrarians by about 1.8 percent per year, on average. The L1M momentum investors actually had slightly higher performance than the L0M momentum investors (although there is a large degree of overlap between the two). The L1M contrarians also achieved better performance than the L0M contrarians, and their performance was statistically significant (but relatively small in magnitude).[16]

Table 2 also shows that the investment-objective categories having the best performance are those that most strongly used a momentum strategy in selecting stocks (see the "total" columns). Of the three categories with significant (at the 99-percent confidence level) performance (aggressive growth, growth, and income funds), two have significantly positive L0M and L1M measures. In fact, among the five major categories, the aggressive-growth category ranks first in performance, L0M, and L1M, while the growth category ranks second in each of these three measures.[17] Interestingly, these

[14] The weights of this zero-investment portfolio represent the difference between the vector of fund portfolio weights in the current period and the vector of fund portfolio weights four quarters earlier. We found that an alternative performance measure which uses a one-quarter lag rather than a four-quarter lag revealed relatively little performance, on average, which indicates that the stocks picked by these funds performed well in the following four quarters, and not simply in the first quarter the stocks were held. This finding rules out the possibility that funds may be affecting their measured performance by heavily buying (or selling) the same stock during consecutive quarters.

[15] Grinblatt and Titman (1993) provide evidence that the two portfolios have the same market betas.

[16] At first glance, it seems surprising that the L1M trend-following and contrarian portfolios both outperform their L0M counterparts. However, this follows from the fact that L1M classifies fewer funds as trend-followers. We expect that the sample of L1M trend-followers will contain stronger trend-followers than the L0M trend-followers. For this reason, the average returns of the L1M trend-followers are higher. In addition, since the L1M contrarians include some of the funds that were classified as trend-followers by the L0M criteria, we also expect the average returns of the L1M contrarians to be higher than the expected returns of the L0M contrarians.

[17] The special-purpose (SP) and the venture-capital/special-situations (VS) categories each had only three funds.

TABLE 2—MEAN PORTFOLIO STATISTICS

	Mean portfolios								
	All 155 funds			Aggressive growth			Balanced		
	Total	Momentum	Contrarians	Total	Momentum	Contrarians	Total	Momentum	Contrarians
A. *Based on L0M statistic:*	(N = 155)	(N = 119)	(N = 36)	(N = 45)	(N = 40)	(N = 5)	(N = 10)	(N = 6)	(N = 4)
L0M (percent/quarter)	0.74	1.06	−0.30	1.25	1.45	−0.31	0.29	0.62	−0.20
	(10.96**)	(10.78**)	(−5.20**)	(9.80**)	(10.07**)	(−2.92**)	(3.83**)	(5.27**)	(−2.18*)
Performance (percent/year)	2.04	2.61	0.15	3.40	3.75	0.63	0.01	0.03	−0.01
	(3.16**)	(3.25**)	(0.51)	(3.55**)	(3.56**)	(0.71)	(0.03)	(0.05)	(−0.03)
Performance of differenced portfolio (percent/ year)		2.46			3.12			0.04	
		(3.32**)			(2.49*)			(0.06)	
B. *Based on L1M statistic:*	(N = 155)	(N = 91)	(N = 64)	(N = 45)	(N = 31)	(N = 14)	(N = 10)	(N = 4)	(N = 6)
L1M (percent/quarter)	0.30	0.74	−0.33	0.53	0.94	−0.38	−0.02	0.35	−0.27
	(5.46**)	(8.81**)	(−7.93**)	(4.18**)	(6.65**)	(−2.48*)	(−0.33)	(2.75**)	(−4.13**)
Performance (percent/year)	2.04	2.79	0.97	3.40	3.92	2.26	0.01	0.16	−0.09
	(3.16**)	(3.02**)	(2.82**)	(3.55**)	(3.14**)	(3.10**)	(0.03)	(0.19)	(−0.23)
Performance of differenced portfolio (percent/ year)		1.81			1.66			0.25	
		(2.44**)			(1.36)			(0.27)	

Notes: For each category, the funds were separated into two sets: those with a positive momentum investing measure ("Momentum"), and those with a negative measure ("Contrarians"). Equally weighted portfolios were then formed, and time-series mean and t statistics are shown in the table. The "differenced portfolio" is long the momentum-investing portfolio and short the contrarian portfolio. Numbers in parentheses are t statistics.

† Statistically significant at the 10-percent level.
* Statistically significant at the 5-percent level.
** Statistically significant at the 1-percent level.

categories also tend to have the highest amount of portfolio turnover and tend to be the smallest in terms of the size of total assets managed. Only the income-fund category shows significant performance and an insignificant level of momentum investing. Other categories of funds show some degree of momentum investing, but their levels are relatively small.

Regression results, all of which control for investment objective, are found in Table 3. The first two regressions show a strong correlation between performance and momentum investing, whether measured with L0M or L1M. For the sample of all 155 funds, the estimated regression coefficient of 1.27 for the first regression indicates that an increase of 1 percent in momentum investing, according to the L0M measure, increases performance by about 1.27 percent.[18]

Multiple regressions of performance on L0M and L1M and of performance on L0M, L1M, L2M, L3M, and L4M show that L0M provides the main explanatory power. This is not surprising, given the high correlation between L0M and the momentum measures based on longer lags. The next two regressions

[18] Note that the turnover-adjusted L0M (TAL0M) was not included as one of these momentum investing measures because it is not a metric of the tendency of a fund to choose a portfolio based on past returns of stocks. TAL0M was only used to compare the tendency of funds to invest on momentum, without regard to differences in the intensity of trading across funds.

TABLE 2—*Extended.*

Mean portfolios								
Growth			Growth–income			Income		
Total	Momentum	Contrarians	Total	Momentum	Contrarians	Total	Momentum	Contrarians
(N = 44)	(N = 36)	(N = 8)	(N = 37)	(N = 25)	(N = 12)	(N = 13)	(N = 8)	(N = 5)
0.89	1.17	−0.39	0.32	0.58	−0.23	0.17	0.48	−0.33
(10.71**)	(10.85**)	(−4.67**)	(6.33**)	(7.44**)	(−2.83**)	(1.63)	(3.77**)	(−2.04*)
2.41	2.82	0.56	0.83	1.19	0.08	1.33	1.85	0.51
(2.94**)	(2.94**)	(1.00)	(1.75†)	(1.99*)	(0.22)	(2.64**)	(2.38*)	(0.81)
	2.26			1.11			1.35	
	(2.37*)			(2.16*)			(1.26)	
(N = 44)	(N = 33)	(N = 11)	(N = 37)	(N = 13)	(N = 24)	(N = 13)	(N = 6)	(N = 7)
0.43	0.73	−0.45	−0.04	0.39	−0.28	0.03	0.37	−0.26
(6.16**)	(8.08**)	(−6.50**)	(−1.01)	(4.99**)	(−4.96**)	(0.36)	(2.69**)	(−2.34*)
2.41	2.69	1.54	0.83	1.34	0.55	1.33	1.88	0.86
(2.94**)	(2.69**)	(3.05**)	(1.75†)	(1.96*)	(1.27)	(2.64**)	(2.19*)	(1.52)
	1.15			0.79			1.02	
	(1.31)			(1.52)			(1.00)	

show that L0M and Sell L0M do not explain performance, after controlling for Buy L0M (similar results are shown for Buy L1M and Sell L1M). This finding is consistent with our prior finding that momentum investing was concentrated in buying large-capitalization winners. The regression in the last row confirms that Buy L0M explains performance better than Buy L1M.

In unreported results, we compared the hypothetical gross (not risk-adjusted) portfolio returns of momentum investors and contrarians with a market benchmark, the value-weighted CRSP index (with daily dividend reinvestment). In calculating gross returns, we assumed that the portfolio indicated by the beginning-of-quarter holdings was held constant until the end of the quarter, when the weights were updated. We found that, in general, momentum investors realized higher gross returns than contrarians, and both realized higher returns than the CRSP index. For example, the mean gross return of the 119 L0M momentum investors was 17.9 percent per year, while that of the 36 contrarian investors was 17.2 percent per year.[19] The mean return of the CRSP index during this period was about 14.7 percent per year. From Table 2A, the average difference between the *risk-adjusted performance* of momentum and contrarian investors was 2.5 percent (per year) during this period, which was higher than the average difference between their *gross returns* (0.7 percent per year). Contrarians held more priced risk in their portfolios by holding smaller stocks than momentum investors.

IV. The Herding Behavior of the Mutual Funds

The preceding analysis indicates that mutual funds show a tendency to buy stocks based on

[19] The top 20 percent of L0M momentum investors had an average hypothetical gross return of 19.0 percent per year, while the bottom 20 percent (the most contrarian investors) had an average return of 17.5 percent per year.

TABLE 3—CROSS-SECTIONAL REGRESSIONS ACROSS ALL 155 FUNDS, DEPENDENT VARIABLE = PERFORMANCE (PERCENT PER YEAR)

Independent variable	Regression (i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
L0M	1.27 (2.67**)		1.15 (2.53*)	1.13 (2.33*)	0.66 (1.00)			
L1M		1.20 (2.02*)	0.27 (0.50)	0.32 (0.58)				
L2M				−0.51 (−0.81)				
L3M				0.31 (0.46)				
L4M				0.44 (0.70)				
Buy L0M					0.94 (1.65†)	1.66 (3.26**)		1.33 (2.48*)
Sell L0M						0.63 (0.84)		
Buy L1M							1.42) (2.22*)	0.44 (0.71)
Sell L1M							0.14 (0.22)	
R^2:	0.03	0.29	0.39	0.39	0.40	0.40	0.34	0.39
F:			3.68 (0.03)	2.49 (0.03)	6.03 (0.003)	6.19 (0.002)	3.66 (0.03)	5.48 (0.01)

Notes: In each regression, the time-series average fund performance (in percent/year) is regressed, cross-sectionally, on the time-series average momentum investing measures (in percent/quarter). For example, in regression (i), the time-series mean performance is regressed, across funds, on the time-series mean L0M measure. The method of computing t and F statistics is based on a time-series procedure (see Grinblatt and Titman [1994] for details). Separate dummy intercepts were used for funds in different investment objective categories to control for differences in non-momentum-investing-related performance across categories. Therefore, the common intercept was fixed at zero. The t statistics are given in parentheses beneath coefficient estimates; numbers in parentheses beneath F statistics are p values.

† Statistically significant at the 10-percent level.

* Statistically significant at the 5-percent level.

** Statistically significant at the 1-percent level.

their past returns. This, by itself, suggests that mutual funds should show some (possibly weak) tendency to herd (i.e., buy and sell the same stocks in the same quarter). For example, we would expect to observe more mutual funds buying than selling those stocks that have recently increased in price. In this section, we examine this tendency to herd more generally.

As a starting point, we replicate the analysis of Lakonishok, Andrei Shleifer, and Robert W. Vishny (1992) (henceforth, LSV) on our sample of mutual funds. LSV calculated a statistic, described by equation (6), that measures the average tendency of pension funds either to buy or to sell particular stocks at the same time:

$$\text{(6)} \quad \mathrm{UHM}_{i,t} = |p_{i,t} - \bar{p}_t| - E|p_{i,t} - \bar{p}_t|$$

where $p_{i,t}$ equals the proportion of funds, trading in stock i during quarter t, that are buyers;

$\bar{p}_t$, which is the expected value of $p_{i,t}$, is calculated as the mean of $p_{i,t}$ over all stocks during quarter t. Therefore, $\bar{p}_t$ is the proportion of fund trades in quarter t that are buys, for the average stock. We refer to the statistic given by equation (6) as the "unsigned herding measure" (UHM) to distinguish it from what we later describe as the "signed herding measure" (SHM), which separates buy and sell herding.

Table 4A presents the mean unsigned herding statistics, averaged over all stock-quarters (see the "total" column) and averaged over two subgroups of stock-quarters (see the "buy" and "sell" columns). Membership of a stock-quarter in one of the subgroups was determined by whether the set of all funds was buying or selling the stock during the quarter to a greater degree than would be expected with random buying and selling (i.e., stock i during quarter t was considered to be a "buy herding" stock-quarter if $p_{i,t} > \bar{p}_t$; similarly, stock "sell herding" categorization occurred when $p_{i,t} < \bar{p}_t$). This partition allows us to determine whether herding was stronger on the buy side than on the sell side of institutional trades. Analogous to LSV, the statistics given in Table 4 are from the perspective of individual stocks (instead of from a fund perspective) and are based on the entire sample of 274 mutual funds (including nonsurvivors) that existed on December 31, 1974. In addition, we segregated the stock-quarters by whether they had a return among the top 50 percent of NYSE and AMEX returns during the quarter, or among the bottom 50 percent.

The herding statistic of 2.5 percent (in Table 4A under the "total" column for all 274 funds) is the unsigned herding measure, averaged over all NYSE and AMEX stock-quarters (where trades by at least one fund occurred in that stock) during the period from December 31, 1974 to December 31, 1984. This overall herding measure can be thought of as meaning that, for the average stock-quarter, if 100 funds traded in that stock-quarter, 2.5 more funds traded on the same side of the market than would be expected under the null hypothesis that the stocks were picked independently. This overall level of herding does not seem economically significant, and it is similar to the mean level that LSV found for pension funds, 2.7 percent.

Not surprisingly, Table 4A shows that the set of all funds exhibits more herding in buying past winners than in buying past losers. However, herding that occurs on the sell side, although positive, appears to be less related to past returns. These findings are consistent with the average fund being a momentum investor that buys past winners but does not systematically sell past losers, which results in several funds herding into (but not out of) the same groups of stocks based on their past-quarter returns.

The average herding measure for the set of all funds appears to be small. Two explanations for this are examined in Table 4. The first has to do with the possibility that we are measuring herding over a sample of investors that is too broad. For example, by definition, all investors cannot be buying and selling as a herd, since, in the aggregate, the buys must equal the sells. As a result, if our sample of mutual funds is representative of a large fraction of trading, then we would not expect to find much evidence of herding. However, herding may exist among various subsets of the mutual funds. For this reason, we also apply the LSV herding measure [equation (6)] to measure imbalances between buys and sells of the smaller subgroups represented by the investment-objective categories. The results in Table 4A indicate that we find even less evidence of herding within investment-objective category subgroups.

A second reason why we may not have found strong evidence of herding is that the herding measure was aggregated across all stock-quarters, including those with very little trading by the mutual funds. Intuitively, it makes sense to condition the herding measure on the number of funds trading in the stock during the particular quarter. It is certainly much more meaningful to analyze the tendency of funds to be either simultaneously buying or selling a particular stock that several funds are trading in a particular quarter than a stock which only a few funds are trading. Because of this, we present the average herding

TABLE 4—MEAN HERDING STATISTICS, SEGREGATED BY PAST-QUARTER-RETURN DECILES AND BY "BUY" OR "SELL" HERDING

Statistic	Total sample of funds (N = 274) Buy	Sell	Total	Aggressive-growth funds (N = 73) Buy	Sell	Total	Balanced funds (N = 19) Buy	Sell	Total
A. *Mean Herding Statistic (Percentage) for Volume of Trade* ≥ *1:*									
Past losers	1.11	3.48	2.29	0.02	3.57	1.98	1.63	−2.22	−0.45
(Number of stock-quarters)	(9,631)	(9,527)	(19,158)	(5,700)	(6,987)	(12,687)	(1,705)	(2,003)	(3,708)
Past winners	2.51	2.85	2.68	1.03	2.66	1.82	0.95	−1.91	−0.51
(Number of stock-quarters)	(11,462)	(11,285)	(22,747)	(7,426)	(6,930)	(14,356)	(1,942)	(2,028)	(3,970)
All stock-quarters	1.87	3.14	2.50	0.59	3.12	1.89	1.26	−2.07	−0.48
(Number of stock-quarters)	(21,093)	(20,812)	(41,905)	(13,126)	(13,917)	(27,043)	(3,647)	(4,031)	(7,678)
B. *Mean Herding Statistic (Percentage) for Volume of Trade* ≥ *5:*									
Past losers	3.11	4.89	4.08	5.18	7.53	6.46	4.92	1.38	3.10
(Number of stock-quarters)	(3,341)	(3.987)	(7,328)	(586)	(700)	(1,286)	(56)	(59)	(115)
Past winners	4.58	4.47	4.53	6.50	5.04	5.80	3.82	−1.26	1.68
(Number of stock-quarters	(4,079)	(4,267)	(8,346)	(823)	(760)	(1,583)	(62)	(45)	(107)
All stock-quarters	3.92	4.68	4.32	5.95	6.23	6.10	4.34	0.23	2.42
(Number of stock-quarters)	(7,420)	(8,254)	(15,674)	(1,409)	(1,460)	(2,869)	(118)	(104)	(222)
C. *Mean Herding Statistic (Percentage) for Volume of Trade* ≥ *10:*									
Past losers	5.26	5.42	5.35	7.86	9.14	8.59	14.55	0.18	8.80
(Number of stock-quarters)	(1,350)	(1,653)	(3,003)	(106)	(138)	(244)	(3)	(2)	(5)
Past winners	5.94	5.35	5.63	9.06	6.77	7.89	6.55	−0.10	3.42
(Number of stock-quarters)	(1,687)	(1,816)	(3,503)	(127)	(132)	(259)	(9)	(8)	(17)
All stock-quarters	5.64	5.38	5.50	8.52	7.98	8.23	8.55	−0.04	4.64
(Number of stock-quarters)	(3,037)	(3,469)	(6,506)	(233)	(270)	(503)	(12)	(10)	(22)

Notes: Past-quarter returns are defined as those returns during the same quarter as the portfolio revisions. Individual herding statistics are calculated as $|p - E(p)| - E|p - E(p)|$, where p = the proportion of funds buying the given stock during the given quarter among all funds that traded that stock during that quarter. $E(p)$ and $E|p - E(p)|$ are calculated under the null hypothesis of no intentional herding. The "mean herding statistic" is the average of the individual herding statistics across time and across stocks, for a given category. The column labeled "total" is the mean herding statistic calculated over all stock-quarters having at least the volume of trade by the funds indicated in the panel. "Buy" is calculated as the average over only those stock-quarters where $p > E(p)$, that is, the proportion of buys was greater than the expected proportion of buys. "Sell" is calculated as the average only over those stock-quarters for which $p < E(p)$. "Past losers" are those stocks having past returns in the lower 50 percent among all NYSE and AMEX stocks during the given quarter, while "past winners" are those having past returns in the upper 50 percent.

measures over all stock-quarters with at least five active funds in Table 4B, and over all stock-quarters with at least ten active funds in Table 4C.

Panels B and C of Table 4 show that, when we limit our analysis to stock-quarters with at least five or ten trades, respectively, evidence of herding increases significantly. For example, for the entire sample of funds, the average herding measure is about 5.5 percent when we include only stock-quarters with at least ten funds active. Note that, when at least ten funds were active, funds in the objective categories with the highest average performance (aggressive growth, growth, and income [see Table 4A]) showed the greatest tendency to herd in the average stock-quarter.

The next step in our analysis is to characterize individual funds by the extent to which they "go with the crowd." In order to measure a particular fund's tendency to herd, we first develop what we call a "signed" stock herding measure (SHM), defined below, which provides an indication of whether a fund is "following the crowd" or "going

TABLE 4—*Extended.*

Growth funds (N = 81)			Growth–income funds (N = 57)			Income funds (N = 31)		
Buy	Sell	Total	Buy	Sell	Total	Buy	Sell	Total
0.60 (6,115)	1.98 (7,147)	1.34 (13,262)	0.76 (5,318)	1.54 (5,525)	1.16 (10,843)	−0.95 (2,709)	3.22 (2,750)	1.15 (5,459)
1.49 (7,258)	2.01 (7,171)	1.75 (14,429)	1.22 (5,637)	2.08 (5,771)	1.66 (11,408)	−1.25 (3,182)	2.64 (3,014)	0.64 (6,196)
1.08 (13,373)	1.99 (14,318)	1.55 (27,691)	1.00 (10,955)	1.81 (11,296)	1.41 (22,251)	−1.11 (5,891)	2.92 (5,764)	0.88 (11,655)
3.73 (916)	3.97 (1,165)	3.87 (2,081)	4.38 (676)	3.26 (700)	3.81 (1,376)	4.27 (73)	3.18 (67)	3.75 (140)
4.50 (1,206)	3.45 (1,205)	3.98 (2,411)	4.29 (718)	4.02 (785)	4.15 (1,503)	3.92 (110)	8.13 (115)	6.07 (225)
4.17 (2,122)	3.71 (2,370)	3.93 (4,492)	4.34 (1,394)	3.66 (1,485)	3.99 (2,879)	4.06 (183)	6.31 (182)	5.18 (365)
5.81 (245)	4.89 (314)	5.30 (559)	6.92 (162)	4.74 (178)	5.78 (340)	7.24 (7)	5.78 (6)	6.57 (13)
7.14 (296)	4.62 (250)	5.98 (546)	4.28 (161)	2.93 (156)	3.62 (317)	5.58 (11)	5.25 (14)	5.39 (25)
6.54 (541)	4.77 (564)	5.64 (1,105)	5.60 (323)	3.89 (334)	4.73 (657)	6.22 (18)	5.41 (20)	5.79 (38)

against the crowd'' in a particular stock during a particular quarter:

$$(7)\quad \mathrm{SHM}_{i,t} = I_{i,t} \times \mathrm{UHM}_{i,t} - E[I_{i,t} \times \mathrm{UHM}_{i,t}]$$

where $\mathrm{SHM}_{i,t} \equiv 0$ if fewer than 10 funds traded stock i during quarter t. Otherwise,

$$I_{i,t} = \begin{cases} 0 & \text{if } |p_{i,t} - \bar{p}_t| < E|p_{i,t} - \bar{p}_t|; \\ 1 & \text{if } p_{i,t} - \bar{p}_t > E|p_{i,t} - \bar{p}_t| \text{ and the mutual fund is a buyer of stock } i \text{ during quarter } t\text{, or if } -(p_{i,t} - \bar{p}_t) > E|p_{i,t} - \bar{p}_t| \text{ and the fund is a seller (i.e., the fund ``follows the crowd'');} \\ -1 & \text{if } p_{i,t} - \bar{p}_t > E|p_{i,t} - \bar{p}_t| \text{ and the mutual fund is a seller of stock } i \text{ during quarter } t\text{, or if } -(p_{i,t} - \bar{p}_t) > E|p_{i,t} - \bar{p}_t| \text{ and the fund is a buyer (i.e., the fund ``goes against the crowd'').} \end{cases}$$

Note that $\mathrm{SHM}_{i,t} = 0$ if a stock-quarter shows negative herding or if only a small number of funds have traded it, since there is no meaningful way in which the fund can herd (or invest against the herd) in these cases. Also, $I_{i,t} = 1$ if the fund trades ''with the herd'' in stock i during quarter t, and $I_{i,t} = -1$ if the fund trades ''against the herd'' in that stock-quarter. The second term in $\mathrm{SHM}_{i,t}$ is calculated under the null hypothesis of no herding by the funds in the stock-quarter (above that due to chance).[20]

[20] Under the null hypothesis of independent trading decisions among funds, the number of trading funds that are buyers is binomially distributed. We can calculate the value of $E(I \times \mathrm{UHM})$ for stock i in quarter t starting with the following known binomial parameters:

TABLE 5—MEAN PORTFOLIO STATISTICS

Measure	Total sample (N = 155)	Aggressive growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
FHM	0.84	1.05	0.66	0.89	0.72	0.60	0.12	0.83
(percent)	(6.73**)	(6.49**)	(5.99**)	(6.95**)	(6.84**)	(4.46**)	(1.92†)	(6.73**)
LOM	0.74	1.25	0.29	0.89	0.32	0.17	−0.05	0.95
(percent/quarter)	(10.96**)	(9.80**)	(3.83**)	(10.71**)	(6.33**)	(1.63)	(−0.33)	(3.17**)
Performance	2.04	3.40	0.01	2.41	0.83	1.33	0.21	2.66
(percent/year)	(3.16**)	(3.55**)	(0.03)	(2.94**)	(1.75†)	(2.64**)	(0.19)	(1.43)

Notes: For each category above an equally weighted portfolio of all funds in that category is formed. Then, for the "fund herding measure" (FHM), we calculate the portfolio-weighted "signed herding measure" (SHM) of the stocks held by that equally weighted portfolio at the end of a quarter, less the portfolio-weighted SHM of the stocks held at the beginning of that quarter, based on the herding measure of the stocks during that quarter. Finally, the time-series mean and t statistic are calculated across all 40 quarters. For the LOM measure, the same procedure is followed, but the portfolio-weighted stock returns are used instead of the portfolio-weighted herding measure (giving a time series of 120 months of data). For the performance measure, we calculate for each quarter the portfolio-weighted stock returns (of the next quarter) based on the end-of-quarter portfolio, less the portfolio-weighted returns (of the next quarter) based on the portfolio held four quarters previously. This procedure gives a time series of 111 months of data. Time-series t statistics are given in parentheses.

† Statistically significant at the 10-percent level.

** Statistically significant at the 1-percent level.

The fund herding measure for an individual fund (FHM) is then calculated by substituting the signed herding measure in place of the stock return in equation (2) (for $k = 1$); that is,

$$\text{(8)} \quad \text{FHM} = \frac{1}{120} \sum_{t=1}^{40} \sum_{i=1}^{3} \sum_{j=1}^{N} (\tilde{w}_{j,3t} - \tilde{w}_{j,3t-3}) \text{SHM}_{j,3t-3+i}.$$

As the above equation illustrates, a positive (negative) portfolio revision is multiplied by a positive (negative) SHM if the set of all funds bought (sold) heavily in a given stock during a given quarter, giving a positive contribution to that fund's FHM. Conversely, a positive (negative) portfolio revision is multiplied by a negative (positive) SHM if the set of all funds sold (bought) heavily in a given stock during a given quarter, giving a negative contribution to that fund's FHM. Hence, funds that tend to buy (sell) when other funds are also buying (selling) will be characterized as herders by this measure.

Table 5 presents the fund herding results. All categories of funds showed highly significant levels of FHM, and unreported F tests strongly rejected that the average FHM fund herding measure is equal across categories, or that it is zero for all categories. We can interpret the reported 0.84 value for FHM as meaning that, if the average fund traded 10 percent of its portfolio each quarter, it bought stocks that, on a portfolio-weighted average, had

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n = the number of funds trading stock i in quarter t,

$\bar{p}$ = the proportion of trading funds in the population that are buyers, estimated as described for equation (6).

Note that in the above expectation UHM = UHM(p), where p = the proportion of funds trading in stock-quarter (i, t) that are buyers. Then, for stock i in quarter t,

$$E[I \times \text{UHM}] = \sum_{p: p-\bar{p} > E|p-\bar{p}|} (2p-1)\text{UHM}(p)\Pr(p) - \sum_{p: -(p-\bar{p}) > E|p-\bar{p}|} (2p-1)\text{UHM}(p)\Pr(p)$$

where, for the n discrete values that p can assume,

$$\Pr(p) = \binom{n}{np} \bar{p}^{np}(1-\bar{p})^{n-np}.$$

TABLE 6—CROSS-SECTIONAL REGRESSIONS OF FUND PERFORMANCE

Independent variable	Total sample (N = 155)	Aggressive growth (N = 45)	Balanced (N = 10)	Growth (N = 44)	Growth–income (N = 37)	Income (N = 13)	Special-purpose (N = 3)	Venture-capital/special-situations (N = 3)
A. *Cross-Sectional Regressions of Fund Performance on Fund Herding Measure (FHM):*								
Constant		2.99	0.21	−0.25	−1.17	2.35	1.60	−2.79
		(3.01**)	(0.33)	(−0.45)	(−2.16*)	(2.44*)	(0.60)	(1.26)
FHM	1.61	0.40	−0.30	2.97	2.78	−1.69	−11.67	9.93
	(2.82**)	(0.57)	(−0.29)	(3.37**)	(2.80**)	(−1.29)	(−.85)	(2.38*)
Adjusted R^2:	0.25	−0.0001	0.02	0.32	0.25	0.04	0.73	0.56
B. *Cross-Sectional Regressions of Fund Performance on LOM and FHM:*								
Constant		2.65	0.20	0.49	−0.35	2.39	—[a]	—[a]
		(3.02**)	(0.30)	(0.67)	(−0.53)	(2.30*)		
LOM	1.24	0.87	−0.02	1.08	1.22	2.86		
	(2.23*)	(1.42)	(−0.02)	(1.54)	(1.91†)	(2.07†)		
FHM	0.12	−0.32	−0.28	1.06	1.10	−0.21		
	(0.20)	(−0.39)	(−0.24)	(1.12)	(1.01)	(−1.79)		
F:	4.39	1.10	0.04	6.00	4.47	2.66		
	(0.01)	(0.34)	(0.96)	(0.003)	(0.01)	(0.07)		
Adjusted R^2:	0.39	0.12	0.02	0.42	0.35	0.39		

Notes: In panel A, for each category, the benchmark-free fund performance measure (percent/year) is regressed, across funds, on the fund herding measure (FHM, as a percentage). In panel B, for each category the benchmark-free fund performance measure (percent/year) is regressed, across funds, on the fund momentum-investing measure (LOM, percent/quarter) and on FHM. The method of computing t and F statistics is given in Grinblatt and Titman (1994). For the regressions across all 155 funds, separate dummy intercepts were used for funds in different investment-objective categories to control for differences in non-regressor-related performance across categories. Therefore, the common intercept was fixed at zero for those regressions. Student t statistics are in parentheses below the coefficient estimates; the numbers in parentheses beneath the F statistics are the associated p values.

[a] Insufficient data.

† Statistically significant at the 10-percent level.

* Statistically significant at the 5-percent level.

** Statistically significant at the 1-percent level.

about 8.4-percent excessive buying by all funds, or sold stocks that, on a portfolio-weighted average, had 8.4-percent excessive selling by all funds (or some combination of these two extreme outcomes); while an average aggressive-growth fund trading 10 percent each quarter bought (sold) stocks with about 10.5-percent excessive buying (selling) by the set of all 155 funds.

Note that aggressive-growth funds had the highest average levels of FHM, LOM, and performance, while the growth funds were second in all three categories (among the five major fund categories). Funds that invest on momentum are more likely to invest in herds and are more likely to perform.

Table 6A presents results for cross-sectional regressions of performance on FHM. The results show that fund performance is significantly correlated with the tendency of a fund to herd (FHM). This finding by itself would support the idea in some theoretical herding papers that informed investors have a tendency to herd (Brennan, 1990; Froot et al., 1992; Hirshleifer et al., 1994). However, this is due to the high correlation between the tendency to herd and the tendency to buy past winners, which was confirmed in an unreported regression of FHM on L0M. Table 6B shows that, at the margin, FHM does not significantly explain fund performance, given the explanatory power already provided by L0M. Therefore, on average, performing funds tend to buy past winners, with herding in past winners apparently occurring as a result.

V. Conclusion

This paper characterizes some of the investment strategies of mutual funds and analyzes how these strategies relate to realized performance. The evidence indicates that mutual funds have a tendency to buy stocks based on their past returns, and that they tend to buy and sell the same stocks at the same time (i.e., herd) in excess of what one would expect from pure chance. The average level of herding and momentum investing was statistically significant, but not particularly large. However, there was a significant degree of cross-sectional dispersion across funds in their tendency to buy past winners and to trade with the herd.

The tendency of individual funds to buy past winners as well as to herd was shown to be highly correlated with fund performance over our period of study. The relation between the tendency to buy past winners and performance was especially strong. On average, those funds following momentum strategies realized significant excess performance, while contrarian funds realized virtually no performance. The relation between a fund's tendency to go with the herd and its performance was less convincing, and it largely disappeared after controlling for the fund's tendency to buy past winners.

This research provides some insights about the extent to which mutual funds are able to profit from their security-analysis efforts. The positive relation between momentum trading and performance suggests that the positive performance of mutual funds observed in Grinblatt and Titman (1989a, 1993) may have been at least partially generated by a simple trading rule rather than by superior information. This suggests that if the momentum profits observed in Jegadeesh and Titman (1993) disappear in the future, then the performance of these funds is likely to diminish.

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