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Author(s): Richard W. Sias
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Institutional Herding

Richard W. Sias
Washington State University

Institutional investors' demand for a security this quarter is positively correlated with their demand for the security last quarter. We attribute this to institutional investors following each other into and out of the same securities ("herding") and institutional investors following their own lag trades. Although institutional investors are "momentum" traders, little of their herding results from momentum trading. Moreover, institutional demand is more strongly related to lag institutional demand than lag returns. Results are most consistent with the hypothesis that institutions herd as a result of inferring information from each other's trades.

Over the past 30 years the fraction of market capitalization held by institutional investors has nearly doubled.[1] The growing institutional presence has led to a common perception that institutional herding (i.e., institutional investors following each other into and out of the same securities) impacts security prices and leads to excess volatility and market fragility. In a recent episode of Wall $treet Week, for example, Louis Rukeyser claimed, "Who really did do the panicking at the bottom? We found what we had long suspected. The real patsies were the large institutional traders who's [*sic*] congenitally shaky nerves get so much sensationalized media attention."[2] Consistent with these assertions, recent studies [Grinblatt and Titman (1989, 1993), Grinblatt, Titman, and Wermers (1995), Wermers (1999, 2000), Nofsinger and Sias (1999), Jones, Lee, and Weis (1999), Cai, Kaul, and Zheng (2000), Sias, Starks, and Titman (2002)] document a strong positive relation between changes in institutional ownership and returns measured over the same period. Moreover,

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[1] Institutional investors accounted for 28% of total U.S. equity ownership in 1970 versus 50% in 1999.

[2] Quoted by Richard Strozinsky (1998). Other examples include (1) a recent Associated Press wire story [Cunniff (2000)] noting, "Institutions, of which mutual funds are numerically the largest segment, account for most of each day's trading and much of the volatility... And so, when you hear of references to investors and what they did in the marketplace, think not of some prototypical individual, but visualize the herd instead," (2) a recent *Detroit Free Press* article [Yue (1998)] noting, "Pull back the stock market curtain and you'll find institutional investors feverishly working the strings," and (3) a recent *New York Times* article [Barboza (1998)] claiming, "The selling was furious early Tuesday ... This surge in activity raises a question: Who exactly is moving the market this summer? The answer: institutional investors... "

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Chakravarty (2001), Dennis and Weston (2000), and Sias, Starks, and Titman (2002) conclude that the relation between changes in institutional ownership and returns measured over the same period results primarily from price effects associated with institutional trading. Although these studies are consistent with the hypothesis that institutions trading in the same direction impact security prices, they do not allow one to conclude institutional investors are herding because some securities will experience net changes in institutional ownership simply by chance.

The primary goal of this article is to examine this important outstanding question: Do institutional investors herd? To investigate this issue, we evaluate the cross-sectional correlation between institutional demand for a security last quarter and institutional demand for the security this quarter. We demonstrate that the fraction of institutions buying this quarter will covary (across securities) with the fraction buying last quarter if institutional investors follow each other into and out of the same securities (herd) or follow themselves into and out of the same securities. Moreover, the cross-sectional correlation between the fraction of institutions buying over adjacent quarters can be directly decomposed into the portion that results from individual institutional investors following their own trades and the portion that results from institutional investors following other institutional investors' trades.

Herding is defined as a group of investors *following* each other into (or out of) the same securities *over some period of time*.[3] Thus tests for herding implicitly or explicitly examine the temporal patterns in the cross section of institutional traders, that is, whether they *follow* each other's trades. The Lakonishok, Shleifer, and Vishny (1992) herding measure, for example, tests for cross-sectional temporal dependence by recognizing that if institutional investors follow each other into (out of) the same stocks over some period of time, institutional investors will be primarily buyers (sellers) of the security over that period. We take a different approach by measuring the cross-sectional temporal dependence directly, that is, the extent to which traders follow each other over adjacent quarters.

The rich theoretical foundation for institutional herding can be divided into five categories—informational cascades, investigative herding, reputational herding, fads, and characteristic herding.[4] Informational

[3] Occasionally herding is referred to as a group of investors buying or selling the same securities "at the same time." Because trades occur sequentially, however, investors cannot buy or sell at the same time. Thus we define herding as a group of traders following each other into (or out of) the same securities over some period. This does not preclude the possibility, however, that a group of investors accumulate positions over the same period. For example, investor A may purchase a security on Monday followed by investor B purchasing the security on Tuesday followed by investor A purchasing more of the security on Wednesday.

[4] See Graham (1999), Nofsinger and Sias (1999), and Wermers (1999) for further discussions of these classifications.

cascades result from institutional investors ignoring their own noisy information and trading with the herd because they infer information from each other's trades [Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992)]. Investigative herding occurs when institutional investors' information is positively cross-sectionally correlated, possibly because they follow the same signals [Froot, Scharfstein, and Stein (1992), Hirshleifer, Subrahmanyam, and Titman (1994)]. Reputational herding is a consequence of institutional investors facing a reputational cost from acting different from the herd [Scharfstein and Stein (1990), Trueman (1994)].[5] Institutional investors may also herd as a result of fads [Freidman (1984), Dreman (1979), Barberis and Shleifer (2001)]. Last, institutional investors may herd because they are attracted to securities with specific characteristics [Falkenstein (1996), Del Guercio (1996), Gompers and Metrick (2001), Bennett, Sias, and Starks (2003)].[6] Thus institutional herding has important implications for how information, agency problems, fads, and security characteristics can affect security selection decisions and asset prices.

Despite these perceptions and strong theoretical foundations, empirical evidence supportive of institutional herding is nearly nonexistent. Lakonishok, Shleifer, and Vishny (1992), for example, conclude, "The emerging image is that institutions follow a broad range of styles and strategies and that their trades offset each other. . . ." Similarly, Grinblatt, Titman, and Wermers (1995) and Wermers (1999) find little evidence of systematic institutional herding. These studies, however, all use the same test for institutional herding—the Lakonishok, Shleifer, and Vishny "herding measure."[7]

Our results, in contrast, reveal compelling evidence of institutional herding. In fact, while previous studies [Grinblatt and Titman (1989, 1993), Grinblatt, Titman, and Wermers (1995), Wermers (1999, 2000), Nofsinger and Sias (1999), Jones, Lee, and Weis (1999), Cai, Kaul, and Zheng (2000), Sias, Starks, and Titman (2002)] document that institutions momentum trade, we demonstrate that institutional demand is more strongly related to lag institutional demand than lag returns. Specifically we find a strong positive relation between the fraction of institutions buying over adjacent quarters, consistent with both institutional herding

[5] It is also possible that some investors engage in herding to minimize litigation risk. Bank trust departments, for example, may defend the prudence of their investment by showing that other bank trust departments also held the security.

[6] Momentum trading serves as an example of characteristic herding, that is, institutional investors are attracted to (repelled by) securities with high (low) past returns.

[7] In an interesting working paper, Pirinsky (2002) takes a different approach to testing for institutional herding by examining time-series correlation (for individual securities) in changes in the fraction of shares held by institutional investors. Consistent with our results, Pirinsky documents a positive relation between this quarter's change in fractional ownership and last quarter's change in fractional ownership.

and institutions following their own lag trades. The decomposition reveals both factors play an important role in explaining the correlation between institutional demand this quarter and last quarter.

The balance of the article focuses on better understanding institutional herding. We begin by examining a special case of characteristic herding—"habit investing." If institutional investors are attracted to securities with the same characteristics, managers will hold many of the same securities. If net flows exhibit positive time-series correlation, net flows are cross-sectionally correlated, and these managers simply proportionally adjust their current portfolio when facing net flows, then these managers will follow each other into and out of the same securities over adjacent quarters, i.e., "herd."

To determine if institutional herding results from habit investing, we focus on the cross-sectional correlation between the fraction of institutions increasing portfolio weights (i.e., the fraction of their assets held in security k) over adjacent quarters. The results reveal little evidence that herding is driven by cross-sectional and time-series correlation in net flows to institutional investors.

We examine returns, momentum trading, and herding by capitalization to further test why institutional investors herd. We document evidence of institutional momentum trading consistent with characteristic herding (i.e., institutional investors are attracted to securities with large lag returns). Momentum trading, however, accounts for little of the herding. Moreover, consistent with recent studies [e.g., Grinblatt and Titman (1989, 1993), Grinblatt, Titman, and Wermers (1995), Wermers (1999, 2000), Nofsinger and Sias (1999), Jones, Lee, and Weis (1999), Sias, Starks, and Titman (2002), Parrino, Sias, and Starks (2003)], we document that institutional demand is positively correlated with contemporaneous returns and weakly positively correlated with returns over the following year. The absence of negative correlation between institutional demand and future returns suggests that herding is primarily related to the way information is incorporated into security prices consistent with informational cascades and investigative herding.

To differentiate informational cascades from investigative herding, we examine herding by capitalization quintile. We use Wermers' (1999) argument that informational cascades are more likely to occur in small-capitalization securities (where signals are noisier). In addition, we posit that investigative herding may be more likely to occur in large-capitalization securities (where signals are less noisy). Although herding occurs in securities of all capitalizations, herding is strongest in small-capitalization securities. Our results are most consistent with models that suggest herding results from institutions inferring information from each other's trades (informational cascades).

We conclude by examining herding over time and by investor type. Specifically we investigate how institutional investors following their own and others' trades changes over time as institutional ownership grows and market liquidity improves. We find evidence that institutional investors are less likely to follow their own lag trades as market liquidity improves. Theoretically it is not clear how increased institutionalization should impact herding. Empirically institutional herding is larger in the 1980s than the 1990s and is primarily driven by a decline in herding in the largest capitalization securities.

Previous studies of herding focus on pension funds [Lakonishok, Shleifer, and Vishny (1992)] or mutual funds [Grinblatt, Titman, and Wermers (1995), Wermers (1999)]. Previous work [e.g., Del Guercio (1996), Bennett, Sias, and Starks (2003)] also reveals that different types of institutional investors operate in different environments (e.g., prudence regulations, holding periods, competition). Differing environments may influence the likelihood that these investors herd. Moreover, as discussed in detail later, several proposed theoretical motives for herding suggest specific differences in herding across investor classifications. Although institutional investors in every classification exhibit statistically significant evidence of herding, we document substantial differences across classifications, with bank trust departments exhibiting the strongest evidence of herding. Moreover, we find some evidence that institutional investors are more likely to follow similarly classified institutional investors than differently classified institutional investors.

The remainder of the article is organized as follows. We discuss the data in the next section. We present tests for institutional herding in Section 2 and examine the possible explanations for institutional herding in Section 3. In Sections 4 and 5 we examine changes in herding over time and differences across investor types, respectively. A summary is presented in the final section.

1. Data

The data for this study come from two sources. Returns, shares outstanding, and firm capitalizations are taken from the Center for Research in Security Prices (CRSP) monthly tapes for all NYSE, AMEX, and NASDAQ stocks. Ownership by each institutional investor for each security comes from CDA-Spectrum and arises from institutional investors' 13F filings. Because 13F reporting is aggregated across different units within an institution, the number of institutions reflects the number of unrelated institutions buying or selling the security.[8] Fidelity Management, for

[8] Institutional investors with $100 million or more under management in exchange-traded or NASDAQ-quoted equity securities are required to file 13F reports within 45 days of the end of the calendar quarter. Institutions are required to report all equity positions greater than either 10,000 shares or $200,000 in market value.

example, files a single 13F report that covers all Fidelity funds. CDA-Spectrum classifies each institutional investor as one of five types—bank trust departments, insurance companies, mutual funds, independent investment advisors, and unclassified institutions.[9] Institutional ownership data are quarterly from March 1983 through December 1997, for a total of 60 quarters.

We begin by calculating, at the beginning and end of each quarter, each institutional investor's position in each security as a fraction of the security's shares outstanding. For each security and quarter, an institutional investor is defined as a buyer if their ownership in the stock increases and a seller if their ownership decreases (e.g., an investor moving from holding 0.01% of IBM's shares to 0.02% of IBM's shares is defined as a buyer).[10] For each stock quarter, we calculate the fraction of institutional investors trading the security that are buyers.[11] We denote this ratio as the "raw fraction of institutions buying" security k during quarter t:

$$Raw\Delta_{k,t} = \frac{No.\ of\ institutions\ buying_{k,t}}{No.\ of\ institutions\ buying_{k,t} + No.\ of\ institutions\ selling_{k,t}}. \tag{1}$$

We run several filters over the data prior to computing the raw fraction of institutions buying. To be included in the sample, a manager must hold at least one security at both the beginning and end of the quarter. Because substantial changes in shares outstanding often accompany changes in CUSIP (committee on uniform security identification procedures) numbers (e.g., mergers), each security is required to have the same beginning- and end-of-quarter CUSIP to be included in the sample. In addition, a security must have at least one institutional investor trading the security during the quarter to be included in the analysis (so the denominator is greater than zero).

The second through sixth columns of Table 1 (panel A) report the total number of institutional investors (overall and by investor type) filing 13F reports at five points in our sample period (approximately every

[9] Unclassified institutions primarily consist of foundations, endowments, employee stock ownership plans (ESOPs), and internally managed pension funds. Managers are defined by CDA-Spectrum based on their majority assets. If, for example, a mutual fund manager also acts as an independent investment advisor, the manager will be classified as a mutual fund manger if at least 50% of their assets are in mutual funds.

[10] Occasionally, due to small changes in the number of shares outstanding, fractional ownership changes slightly while the number of shares held by the investor does not. Therefore if the fraction of shares held by a given investor is the same at the beginning and end of the quarter or if the number of shares held by a given investor is the same at the beginning and end of the quarter, the investor is classified as neither a buyer nor a seller.

[11] Because we can only observe institutional ownership at the quarter end, a manager that buys and sells the same number of shares *within* a quarter will not be counted as a trader.

Table 1
Descriptive statistics

	Average all periods	June 1983	Dec. 1986	Sept. 1990	June 1994	Dec. 1997
Panel A: Number of institutional investors						
No. of Institutions	894	556	703	908	1074	1274
No. of Banks	189	198	190	200	189	164
No. of insurance companies	66	61	63	68	70	68
No. of mutual funds	58	46	50	56	61	81
No. of independent advisors	502	173	325	491	681	892
No. of Unclassified	79	78	75	93	73	69
Panel B: Average number of securities with:						
$\geq$1 trader	5505	3863	4697	5040	6512	7437
$\geq$5 traders	3783	2246	3055	3262	4710	5745
$\geq$10 traders	2851	1654	2209	2432	3658	4464
$\geq$20 traders	1966	1143	1430	1637	2519	3308
$\geq$5 bank traders	4623	1563	1979	1812	2867	3267
$\geq$5 insurance company traders	3080	500	569	787	1261	1898
$\geq$5 mutual fund traders	2863	366	323	641	1150	2481
$\geq$5 independent advisor traders	5033	1522	2215	2616	3795	4742
$\geq$5 unclassified traders	2305	320	534	667	882	1029
Panel C: Average number of securities held by each manager						
All institutions	273	224	249	259	300	332
Banks	440	293	391	395	521	625
Insurance companies	329	202	211	295	422	567
Mutual funds	313	182	174	241	368	659
Independent advisors	211	213	201	203	220	227
Unclassified	245	112	183	245	294	383

Each quarter between March 1983 and December 1997 we calculate the number of institutional investors (overall and by type), the number of securities traded by at least 1, 5, 10, or 20 institutional investors, the number of securities traded by at least 5 institutional investors of each type of institution, and the cross-sectional average number of securities held by each institutional investor (overall and by manager type). Panels A, B, and C report the time-series averages of these figures as well as their values (at approximately) every 15 quarters. Because 13F reporting is aggregated across different units within an institution, the number of institutions reflects the number of unrelated institutions buying or selling the security. Fidelity Management, for example, files a single 13F report that covers all Fidelity funds.

15 months). The first column reports the time-series average across all 59 quarters.[12] Panel B reports the number of securities with at least 1, 5, 10, or 20 institutional traders, as well as the number of securities with at least 5 traders of each type. Panel C reports the average number of securities held by each investor across all institutions and by each type of institution. On average there are 894 managers and 5505 securities with at least one institutional trader each quarter. The average manager holds 273 securities in their portfolio. Consistent with Gompers and Metrick (2001), the results in Table 1 reveal substantial growth in the number of institutions required to file 13F reports, primarily driven by the growth in independent investment advisors.

[12] Sixty quarters of data yield 59 quarters in which we can measure the raw fraction of institutions buying, that is, we require beginning- and end-of-quarter values.

2. Tests for Institutional Herding

If institutional investors follow each other into and out of the same securities (herd), or if individual institutional investors follow their own last-quarter trades, then the fraction of institutions buying in the current quarter will be positively correlated with the fraction of institutions buying in the previous quarter. To allow for aggregation over time and to directly compare coefficients in our investigation of momentum trading [Equation (8)], across capitalizations, different measures of institutional demand, and investor types, we standardized both the dependent and independent variables such that both have zero mean and unit variance.[13] Specifically we define the standardized fraction of institutions buying security k in quarter t (denoted $\Delta_{k,t}$) as

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})}, \tag{2}$$

where $\overline{Raw\Delta_t}$ is the cross-sectional average (across K securities) raw fraction of institutions buying in quarter t and $\sigma(Raw\Delta_{k,t})$ is the cross-sectional standard deviation (across K securities) of the raw fraction of institutions buying in quarter t.[14] Because standardization is simply a linear rescaling, correlations between the variables and the R^2s associated with the regressions are not affected.

2.1 Does institutional demand predict institutional demand?

We begin the analysis by estimating, each quarter, a cross-sectional (across K securities) regression of the standardized fraction of institutions buying security k ($\Delta_{k,t}$) in the current quarter on the standardized fraction of institutions buying security k the previous quarter ($\Delta_{k,t-1}$):[15]

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}. \tag{3}$$

The average coefficient from the 58 regressions and associated t-statistic (computed from the time-series standard error) are reported in the first

[13] Aggregation or direct comparison of raw data regression coefficients across time, independent variables, different measures of institutional demand, capitalization quintiles, or investor types is inappropriate because coefficients depend on the scale of the data.

[14] From a practical standpoint, however, such standardization has little effect on the slope coefficient given in Equation (3). For example, using raw data, the average coefficient associated with the lag raw fraction of institutions buying [see Equation (1)] is 0.1193 (t-statistic = 12.79) which is partitioned [see Equation (4)] into a following-their-own-trades component of 0.0614 (t-statistic = 7.31) and a herding component of 0.0579 (t-statistic = 10.24). This is not surprising because both the dependent and independent variables are divided by the cross-sectional standard deviation of the raw fraction of institutions buying (at time t and $t-1$, respectively). Because the cross-sectional standard deviations of the raw fraction of institutions buying are similar at time t and $t-1$, standardization will not have a large impact on the slope coefficient. Subtracting the mean in Equation (2) does not affect the slope coefficients (i.e., it simply scales the intercept to zero).

[15] Because both the dependent and independent variables are rescaled to zero mean, the intercept is zero.

Table 2
Tests for herding—buyer if increased position

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$$

	Partitioned slope coefficient		
Average coefficient (β)	Institutions following their own trades	Institutions following others' trades	Average R^2
Panel A: Securities with ≥ 1 institutional trader			
0.1194	0.0617	0.0576	1.93%
(12.67)**	(7.33)**	(10.12)**	
Panel B: Securities with ≥ 5 institutional traders			
0.1755	0.0674	0.1081	3.05%
(25.54)**	(17.72)**	(18.90)**	
Panel C: Securities with ≥ 10 institutional traders			
0.1727	0.0554	0.1173	3.16%
(30.78)**	(23.32)**	(23.62)**	
Panel D: Securities with ≥ 20 institutional traders			
0.1602	0.0414	0.1188	2.73%
(29.86)**	(25.42)**	(23.96)**	

For each security and quarter between March 1983 and December 1997 we calculate the fraction of institutional traders that increase their position in the security. An investor is defined as increasing their position if they hold a greater fraction of the firm's shares at the end of the quarter than they held at the beginning. All data are standardized (i.e., rescaled to zero mean, unit variance) each quarter. We then estimate 58 quarterly cross-sectional regressions of institutional demand on lag institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lag institutional demand. The first column reports the time-series average of these 58 correlation coefficients and associated t-statistic (in parentheses, computed from time-series standard errors). The second and third columns report the portion of the correlation [see Equation (4)] that results from institutional investors following their own lag trades and the portion that results from institutions following the previous trades of other institutions (herding). Panels B, C, and D report the averages when limiting the sample to securities with at least 5, 10, or 20 institutional traders, respectively. **Indicates statistical significance at the 1% level; *indicates statistical significance at the 5% level.

column of Table 2 (panel A).[16] The results reveal strong evidence that institutional investors follow other institutional investors and/or themselves into and out of the same securities. The coefficient associated with the lag standardized fraction of institutions buying averages 0.1194 and differs significantly from zero at the 1% level. Because the data are standardized and there is a single independent variable, the coefficients in the regressions of institutional demand on lag institutional demand have a straightforward interpretation—the coefficients are the correlations (see the appendix for the proof). That is, the cross-sectional correlation between institutional demand this quarter and last-quarter averages 0.1194.

[16] Because the regression is of the fraction of institutions buying on the lag fraction buying, we estimate 58 cross-sectional regressions from 60 quarters of data.

2.2 Following their own or others' trades?

The correlation between institutional demand this quarter and institutional demand last quarter has two components. First, the positive correlation could result from institutional investors following each other into and out of the same securities (i.e., herding) over adjacent quarters. Second, the positive correlation could result from individual institutional investors following themselves into and out of the same securities over adjacent quarters.[17]

More formally, because the fraction of institutions buying can be written as a sum across institutional investors, the correlation between the current quarter's and lag quarter's fraction of institutions buying computed from N institutional investors across K securities can be decomposed into the portion that results from an institutional investor following themselves into and out of the same securities over adjacent quarters and the portion that results from institutional investors following other institutional investors into and out of the same securities. Specifically the fraction of traders that are buyers can be written as the sum of a series of dummy variables for each trader (that equal one if the trader is a buyer and zero if the trader is a seller) divided by the number of traders. As a result, the slope coefficient in Equation (3) can be written as (see the proof in the appendix):

$$\begin{aligned}
\beta_t &= \rho(\Delta_{k,t}, \Delta_{k,t-1}) \\
&= \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] \\
&\quad \times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \frac{\left(D_{n,k,t} - \overline{Raw\Delta_t}\right)\left(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{N_{k,t}N_{k,t-1}}\right] \\
&\quad + \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] \\
&\quad \times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \sum_{m=1,m\neq n}^{N_{k,t-1}} \frac{\left(D_{n,k,t} - \overline{Raw\Delta_t}\right)\left(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{N_{k,t}N_{k,t-1}}\right], \qquad (4)
\end{aligned}$$

[17] Assume, for example, there is only one institutional investor and that investor reduces his IBM position in quarters one and two and increases his Microsoft position in the same quarters. For this lone investor and two securities, the fraction of institutions buying in the first quarter will be positively correlated (across securities) with the fraction of institutions buying in the second quarter. For this extreme example, the cross-sectional (population) covariance of the raw fraction of institutions buying is 0.25, that is, the fraction of institutions buying IBM is 0% in quarters one and two and 100% for Microsoft in quarters one and two. Thus the covariance is $((0-0.5)(0-0.5)+(1-0.5)(1-0.5))/2 = 0.25$. The cross-sectional standard deviation (at both time t and $t-1$) of the raw fraction of institutions buying is $((0-0.5)^2+(1-0.5)^2)^{1/2} = \sqrt{0.25}$. Thus the correlation between the raw or standardized fraction of institutions buying is one.

where $N_{k,t}$ is the number of institutional investors trading stock k in quarter t and $D_{n,k,t}$ is a dummy variable that equals one (zero) if trader n is a buyer (seller) of security k in quarter t. Similarly $N_{k,t-1}$ is the number of institutional investors trading stock k in quarter $t-1$, $D_{n,k,t-1}$ is a dummy variable that equals one (zero) if trader n is a buyer (seller) of security k in quarter $t-1$, and $D_{m,k,t-1}$ is a dummy variable that equals one (zero) if trader m ($m \neq n$) is a buyer (seller) of security k in quarter $t-1$.

The first term on the right-hand side of Equation (4) is the portion of correlation [or equivalently, the portion of the slope coefficient in Equation (3)] that results from institutional investors following themselves into and out of the same securities. If institutional investors tend to follow their own trades over adjacent quarters, the first term on the right-hand side of Equation (4) will be positive, that is, if investor n buys security k in quarters t and $t-1$ or sells security k in both quarters, the first term will be positive. Alternatively, if individual institutional investors' transactions this quarter are independent of their own transactions last quarter, the first term will be zero. The first term will be negative if institutional investors tend to reverse their last quarter's transactions.

The second term on the right-hand side of Equation (4) is the portion of the correlation that results from institutional investors following other institutional investors. This term will be positive if institutional investors tend to follow each other into and out of the same securities, that is, if investor m buys (sells) security k in quarter $t-1$ and investor n buys (sells) security k in quarter t, the second term will be positive. If institutional investors tend to abandon (accumulate) securities that other institutional investors purchased (sold) the previous quarter, this term will be negative. If institutional investors' transactions this quarter are independent of other institutional investors' transactions last quarter, this term will be zero.

Time-series averages of each term in Equation (4) and associated t-statistics (computed from time-series standard errors) are reported in the second and third columns in panel A of Table 2. The results reveal that, on average, about half of the correlation (i.e., 0.0617/0.1194) between the fraction of institutions buying this quarter and the fraction buying last-quarter results from individual institutional investors continuing to buy (sell) the securities they bought (sold) the previous quarter (statistically significant at the 1% level). Similarly herding accounts for about half the correlation (i.e., 0.0576/0.1194) between the fraction of institutions buying this quarter and last quarter (statistically significant at the 1% level).[18] Thus the results reveal that institutional investors follow themselves and each other (herd) into and out of the same securities.

[18] The relative importance of each component is further investigated in Section 3.4.

2.3 Additional tests: herding and the number of institutional traders

Because the regressions are estimated from the cross section of securities with at least one institutional trader, it is possible that our results are driven by securities with relatively few institutional traders. For example, the fraction of institutions buying a given security this quarter may be strongly related to the fraction buying the security last quarter because the only institution trading the security last quarter was a buyer and the only two traders this quarter were buyers. Such a security will contribute more to the cross-sectional correlation than a security that had 90% of 100 traders buying last quarter and 90% of 200 traders buying this quarter.[19] To consider this possibility, we repeat the analysis reported in panel A of Table 2 but restrict the sample to those securities with at least 5, 10, or 20 institutional traders.

Contrary to the example provided in the previous paragraph, restricting the sample to securities with at least five institutional traders (panel B of Table 2) yields an even stronger average correlation between the fraction of institutions buying this quarter and the fraction of institutions buying last quarter. Moreover, both components of the correlation—institutions following their own trades and institutions following other institutions' trades—are greater in panel B than panel A. Restricting the sample to securities with an even greater number of traders (i.e., panels C and D), however, does not yield substantial change in the coefficients.

2.4 Comparison with previous work

Contrary to previous studies, we document strong evidence of institutional herding. It is possible, however, that differences between earlier results and our own arise from different samples rather than different methodologies. To disentangle differences in methodology from differences in samples, we compute the Lakonishok, Shleifer, and Vishny (1992) herding measure for our sample.

As noted in the introduction, Lakonishok, Shleifer, and Vishny (1992) test for cross-sectional temporal dependence in institutional demand by recognizing that if institutional investors follow each other into (out of) the same securities over some period of time, then institutional investors will primarily be buyers (sellers) of those securities over that time period. Specifically the Lakonishok, Shleifer, and Vishny herding measure for security k in quarter t is defined as

$$H_{k,t} = |Raw\Delta_{k,t} - \overline{Raw\Delta_t}| - AF_{k,t}, \tag{5}$$

where the raw fraction of institutions buying is as defined in Equation (1) and $\overline{Raw\Delta_t}$ is the cross-sectional average (across K securities) raw fraction

[19] That is, the product of $\Delta_{k,t}$ and $\Delta_{k,t-1}$ in Equation (17) in the appendix would be larger for the first security than the second.

of institutions buying in quarter t as in Equation (2). To demonstrate how the Lakonishok, Shleifer, and Vishny (1992) measure captures cross-sectional temporal dependence, assume that, within a given quarter, institutional investors are just as likely to be buyers as sellers (i.e., $\overline{Raw\Delta_t} = 0.5$). If in *each* security institutional investors do not *follow* each other's trades *within* the quarter (i.e., cross-sectional temporal independence), the number of institutional buyers will, on average, equal the number of institutional sellers and $Raw\Delta_{k,t} - \overline{Raw\Delta_t}$ will tend toward zero. Alternatively, if within *each* security institutional investors tend to *follow* each other into (or out of) the security *within* the quarter (i.e., cross-sectional temporal dependence), $Raw\Delta_{k,t} - \overline{Raw\Delta_t}$ will be nonzero (i.e., positive if institutions follow other institutions into a given security and negative if institutions follow other institutions out of a given security) and the absolute value will be greater than zero for most securities.

The last term in Equation (5), $AF_{k,t}$ (adjustment factor for security k in quarter t), accounts for the fact that even if institutional trades exhibit cross-sectional temporal independence, the expected value of the absolute value of $Raw\Delta_{k,t} - \overline{Raw\Delta_t}$ is greater than zero. That is, simply by chance (or an odd number of traders) there will often be more or fewer buyers than sellers. $AF_{k,t}$ is computed for each security-quarter in which there is at least one institutional trader by assuming the number of institutional investors buying security k in quarter t follows a binomial distribution with probability $\overline{Raw\Delta_t}$.[20]

The average Lakonishok, Shleifer, and Vishny (1992) herding measure across our pooled cross-sectional time-series sample of 324,770 security-quarters that experienced at least one institutional buyer or seller is 0.0178—slightly less than the 0.0270 average reported by Lakonishok, Shleifer, and Vishny. When we restrict the measure to those stocks with at least 5, 10, or 20 institutional investors trading, the average increases, but remains similar to the averages reported by Lakonishok, Shleifer, and Vishny.[21] We conclude that differences between previous studies and our own do not result from differences in samples.

The key difference is the Lakonishok, Shleifer, and Vishny (1992) measure indirectly tests for cross-sectional temporal dependence by recognizing that *within* a period, later institutional traders *following* earlier institutional investors' trades will result in most institutional traders on one side of the trade within that period. Alternatively, we directly test whether institutional investors *follow* each other's trades by examining the

[20] See Lakonishok, Shleifer, and Vishny (1992) for a detailed discussion of their herding measure and computation of the adjustment factor.

[21] For our data, the average Lakonishok, Shleifer, and Vishny (1992) herding measures for the samples limited to 5, 10, or 20 traders are 0.0246, 0.0283, and 0.0329, respectively. All averages differ significantly from zero at the 1% level.

cross-sectional correlation between institutional investors' trades in one period and other institutional investors' trades the next period.

3. Why do Institutional Investors Herd?

We note five possible motives for institutional herding in the introduction: informational cascades, investigative herding, reputational herding, characteristic herding (including habit investing), and fads. These motives, of course, are not mutually exclusive—institutional investors may herd for a number of reasons. Nonetheless, in this section we evaluate habit investing, momentum trading, returns, and differences across capitalizations in an attempt to discriminate between these models.

3.1 Habit investing

A special case of characteristic herding may drive the results—herding could result from cross-sectional and time-series correlation in the net flow of funds to groups of institutional investors.[22,23] Specifically, if some investors experience positive time-series correlation in their net flows and simply invest (divest) flows into (from) their existing portfolios, then these investors will follow themselves into (when flows over consecutive quarters are positive) and out of (when flows over consecutive quarters are negative) the same securities over adjacent quarters. Moreover, if (1) subsets of institutional investors favor securities with specific characteristics (and therefore hold many of the same securities), (2) flows to these investors exhibit positive time-series and cross-sectional correlation, and (3) these investors simply invest (divest) flows into (from) their existing portfolios, then these investors will tend to follow each other into (when flows over consecutive quarters are positive) and out of (when flows over consecutive quarters are negative) the same securities over adjacent quarters.[24]

[22] Habit investing is a special case of characteristic herding because institutional investors follow each other into and out of the same stocks (herd) as a result of their attraction to securities with the same characteristics that cause them to hold similar portfolios. If there were no relation between security characteristics and institutional ownership (i.e., each institution's security preferences were independent of every other institution's preferences), time-series and cross-sectional correlation in the net flows to investors would not result in herding.

[23] The possibility that habit investing explains herding is not unique to our tests. For example, if net flows to subsets of institutional investors exhibit positive cross-sectional correlation and these investors favor specific stocks (e.g., the securities they already hold), the Lakonishok, Shleifer, and Vishny (1992) measure should be positive.

[24] These patterns could occur across similar managers within a classification. For example, technology-oriented mutual funds may experience a net inflow of funds over consecutive quarters, while a set of mutual funds that focus on utility stocks experience a net outflow of funds over the same quarters.

To test whether habit investing explains herding and following their own lag trades, we examine the correlation between the fraction of institutions increasing their portfolio weights this quarter and last. If institutional investors follow themselves and each other into and out of the same securities as a result of habit investing, then portfolio weights should be independent over adjacent quarters. For example, if money were flowing into technology funds, technology funds would be buyers of Microsoft. However, if these mutual funds buy additional shares of Microsoft in proportion to their current holdings, the funds' Microsoft portfolio weights would not change. Alternatively, if institutional investors follow themselves and each other into the same securities for reasons other than time-series and cross-sectional correlation in net flows, then the fraction of institutions increasing portfolio weights will be positively correlated over adjacent quarters.

We focus on changes in "return-adjusted" portfolio weights rather than changes in raw portfolio weights to purge return-induced noise from the measure of the fraction of institutions increasing portfolio weights.[25] The return-adjusted portfolio weight is defined as what the end-of-quarter portfolio weight would be if the investor did not rebalance her portfolio.[26] We begin by defining $V_{n,k,t}$ as the value of investor n's position in security k at the end of the quarter t (i.e., price at the end of quarter t times the number of shares held by investor n at the end of quarter t). Investor n is classified as increasing their return-adjusted portfolio weight (i.e., a

Alternatively, these flows may occur across classifications. Specifically, consistent with Gompers and Metrick (2001), Table 1 demonstrates that markets have experienced substantial differences in the growth rates of different institutional investor classes. Moreover, while recent work [Falkenstein (1996), Del Guercio (1996), Gompers and Metrick (2001), Bennett, Sias, and Starks (2003)] demonstrates that institutional investors are attracted to securities with specific characteristics, these preferences differ across classifications [Del Guercio (1996), Bennett, Sias, and Starks (2003)]. For example, mutual funds may experience a net inflow of funds over consecutive quarters, while bank trust departments experience a net outflow of funds over the same quarters. In this case institutional investors (as a group) would herd to those securities favored by mutual funds and out of securities favored by bank trust departments.

[25] We focus on return-adjusted portfolio weights because the fraction of institutions increasing raw portfolio weights is highly correlated with same-period returns (the cross-sectional correlation between the fraction of institutions increasing their raw portfolio weight and same-quarter returns is 61%, on average). For example, if the investor begins with an equal-weighted portfolio, a stock that experiences a return greater than the average return of other stocks in the investor's portfolio will exhibit a larger portfolio weight at the end of the quarter than the beginning if the investor does not rebalance the portfolio.

[26] Intuitively one may expect institutional investors to sell securities that have increased in value to rebalance their portfolios toward initial weights. Extant work, however, documents strong positive correlation between institutional demand and same-quarter returns, inconsistent with the expected negative correlation associated with rebalancing. It is possible, however, that the positive correlation is driven by new traders rather than existing shareholders. To consider this possibility, we compute the quarterly cross-sectional correlation between the fraction of existing institutional shareholders that are trading who are buyers and returns the same quarter. We find positive correlation between existing shareholder demand and same-quarter returns, inconsistent with the expected negative correlation associated with rebalancing.

buyer) if their end-of-quarter portfolio weight is greater than their return-adjusted beginning-of-quarter portfolio weight:

$$\frac{V_{n,k,t}}{\sum_{k=1}^{K} V_{n,k,t}} > \frac{V_{n,k,t-1}(1+R_{k,t})}{\sum_{k=1}^{K} V_{n,k,t-1}(1+R_{k,t})}, \tag{6}$$

where $R_{k,t}$ is the return for security k over quarter t. Investor n is classified as a seller if the sign is reversed in Equation (6). If an investor buys or sells shares in direct proportion to their portfolio weights at any time during the quarter, the left- and right-hand sides of Equation (6) will be equal and the investor will not be classified as a buyer or a seller.

We then compute the number of institutional investors that increase their return-adjusted portfolio weight as a fraction of the institutional investors that increase or decrease their return-adjusted portfolio weight for the security. Thus the raw fraction of institutions increasing their security k return-adjusted portfolio weights in quarter t is defined as

$$\begin{aligned} &RawRAPW\Delta_{k,t} \\ &\quad = (No.\ of\ institutions\ with\ increased\ return\text{-}adjusted\ weight_{k,t}) \\ &\qquad /(No.\ of\ institutions\ with\ increased\ return\text{-}adjusted\ weight_{k,t} \\ &\qquad\quad + No.\ of\ institutions\ with\ decreased\ return\text{-}adjusted\ weight_{k,t}). \end{aligned} \tag{7}$$

As before, we standardize the data [i.e., analogous to Equation (2)], estimate cross-sectional regressions of the standardized fraction of institutions that increase their return-adjusted portfolio weights on the lag standardized fraction of institutions that increase their return-adjusted portfolio weights [i.e., analogous to Equation (3)], and decompose the slope coefficient [i.e., analogous to Equation (4)].

The time-series average correlation (or, equivalently, slope coefficient), its components, and associated t-statistics (computed from time-series standard errors) are reported in panel A of Table 3. The results reveal that the fraction of institutions increasing their return-adjusted portfolio weights is strongly correlated over adjacent quarters. Similar to the results in Table 2, the correlation between the fraction of institutional investors increasing their return-adjusted portfolio weights and the lag fraction is about equally attributed to individual institutional investors following their own return-adjusted portfolio weight changes (0.0615/0.1195) and following other institutional investors' return-adjusted portfolio weight changes (0.0580/0.1195). The results are inconsistent with the hypothesis that institutional herding is primarily driven by institutional investors' desire to hold their existing portfolios and cross-sectional and time-series correlations in institutional investors' net flows (i.e., habit investing).

Table 3
Tests for herding—buyer if increased return-adjusted portfolio weight

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$$

Average coefficient (β)	Partitioned slope coefficient: Institutions following their own trades	Partitioned slope coefficient: Institutions following others' trades	Average R^2
Panel A: Securities with ≥ 1 institutional trader			
0.1195	0.0615	0.0580	2.38%
(9.26)**	(4.57)**	(8.61)**	
Panel B: Securities with ≥ 5 institutional traders			
0.2048	0.0675	0.1373	4.63%
(23.38)**	(9.25)**	(15.21)**	
Panel C: Securities with ≥ 10 institutional traders			
0.2476	0.0565	0.1910	6.44%
(33.67)**	(14.52)**	(26.40)**	
Panel D: Securities with ≥ 20 institutional traders			
0.2959	0.0446	0.2513	9.01%
(43.64)**	(22.23)**	(38.59)**	

For each security and quarter between March 1983 and December 1997 we calculate the fraction of institutional traders that increase their return-adjusted portfolio weight in the security. An institution is defined as increasing their return-adjusted portfolio weight if the security's weight in the investor's portfolio at the end of the quarter is larger than what it would be if the manager did not rebalance their beginning-of-quarter portfolio. All data are standardized (i.e., rescaled to zero mean, unit variance) each quarter. We then estimate 58 quarterly cross-sectional regressions of institutional demand on lag institutional demand. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between institutional demand and lag institutional demand. The first column reports the time-series average of these 58 correlation coefficients and associated *t*-statistic (in parentheses, computed from time-series standard errors). The second and third columns report the portion of the correlation [see Equation (4)] that results from institutional investors following their own lag trades and the portion that results from institutions following the previous trades of other institutions (herding). Panels B, C, and D report the averages when limiting the sample to securities with at least 5, 10, or 20 institutional traders, respectively. **Indicates statistical significance at the 1% level; *indicates statistical significance at the 5% level.

Moreover, the results are inconsistent with the hypothesis that institutional investors follow their own lag trades as a result of time-series correlation in their net flows and investing flows into their existing portfolios.[27,28]

[27] We also examine the time series of net flows to individual institutional investors and find little evidence of systematic positive time-series correlation. Specifically, we limit the sample to managers with at least 20 quarters of data and define the quarterly net flow to each manager as the difference between the value of their end-of-quarter total equity position and their return-adjusted beginning-of-quarter portfolio value (i.e., what their portfolio would be worth at the end of the quarter if they did not trade and experienced zero net flows). We then estimate time-series regressions of quarterly net flows on lag quarterly net flows for each manager. Of the 1097 managers with sufficient data, 52% exhibit positively correlated net flows and 48% exhibit negatively correlated net flows. The average time-series autocorrelation in quarterly net flows is 0.0224. Ninety percent (88%) of the negative (positive) autocorrelations do not differ significantly from zero at the 5% level or better.

[28] As a robustness test of the importance of time-series and cross-sectional correlation in net flows, we compute a more restrictive definition of buyers and sellers. Specifically, to be defined as a buyer, an investor must purchase additional shares (i.e., satisfy the first definition) and the purchase must be large enough that the security accounts for more of the investor's portfolio at the end of the quarter than at the beginning of the quarter after adjusting for the security's return (i.e., satisfy the second definition).

As with the first regression, we restrict the sample to those securities with at least 5, 10, or 20 institutions changing their return-adjusted portfolio weights. The time-series average correlations, correlation components, and associated t-statistics (computed from time-series standard errors) are reported in panels B–D of Table 3. As before, the results reveal that evidence that institutional investors follow their own and others' lag trades is stronger when the sample excludes securities with little institutional trading.

In sum, the analysis of changing portfolio weights is inconsistent with the habit-investing explanation. Institutional investors appear to herd for reasons other than time-series and cross-sectional correlation in their net flows.

3.2 Momentum trading

Recent work [e.g., Grinblatt and Titman (1989, 1993), Grinblatt, Titman, and Wermers (1995), Jones, Lee, and Weis (1999), Nofsinger and Sias (1999), Wermers (1999, 2000), Sias, Starks, and Titman (2002)] suggests institutional investors are momentum traders. Institutional momentum trading is a form of characteristic herding, that is, institutional investors herd to (away from) stocks with high (low) past returns. Moreover, interquarter herding may result from institutional investors' momentum trading, because the fraction of institutions buying is positively correlated with same-quarter returns. That is, institutional investors may follow each other into and out of the same stocks because institutional investors are momentum traders and the lag fraction of institutions buying proxies for lag return. On the other hand, extant evidence of institutional momentum trading may result from institutional herding, that is, institutional investors may herd to (away from) stocks with large (small) lag returns because institutional demand is correlated with lag institutional demand and lag returns proxy for lag institutional demand.

To evaluate momentum trading and its role in explaining the relation between the fraction of institutions buying and the lag fraction of institutions buying, we add lag return as a standardized independent variable to Equation (3). Specifically, each quarter we cross-sectionally regress (across K securities) the quarterly standardized fraction of institutions buying on the lag quarterly standardized fraction of institutions buying and lag quarterly standardized return:[29]

$$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t}. \tag{8}$$

Similarly, to be defined as a seller, an investor must decrease their position in the security and decrease their return-adjusted portfolio weight. The results remain qualitatively identical to those reported in Table 3.

[29] Standardized return is calculated by replacing the fraction of institutions buying with the return in Equation (2).

Table 4
Standardized regression of institutional demand on lag institutional demand and lag return

$$\Delta_{k,t} = \beta_{1,t}\Delta_{k,t-1} + \beta_{2,t}R_{k,t-1} + \varepsilon_{k,t}$$

Average coefficient associated with lag institutional demand (β_1)	Average coefficient associated with lag return (β_2)	Average R^2
Panel A: Securities with ≥ 1 institutional trader		
Regression 1—Buyer if increased position		
0.1133	0.0691	2.59%
(11.84)**	(12.10)**	
Regression 2—Buyer if increased return-adjusted portfolio weight		
0.1154	0.0545	2.86%
(9.00)**	(9.42)**	
Panel B: Securities with ≥ 5 institutional traders		
Regression 1—Buyer if increased position		
0.1624	0.0789	4.19%
(22.25)**	(11.90)**	
Regression 2—Buyer if increased return-adjusted portfolio weight		
0.1953	0.0774	5.50%
(22.32)**	(10.89)**	
Panel C: Securities with ≥ 10 institutional traders		
Regression 1—Buyer if increased position		
0.1590	0.0671	3.90%
(26.26)**	(8.98)**	
Regression 2—Buyer if increased return-adjusted portfolio weight		
0.2340	0.0801	7.34%
(31.97)**	(11.16)**	
Panel D: Securities with ≥ 20 institutional traders		
Regression 1—Buyer if increased position		
0.1490	0.0476	3.23%
(26.90)**	(6.54)**	
Regression 2—Buyer if increased return-adjusted portfolio weight		
0.2802	0.0658	9.79%
(42.75)**	(8.04)**	

For each security and quarter between March 1983 and December 1997 we calculate the fraction of institutional traders that increase their position in the security and the fraction that increase their return-adjusted portfolio weight in the security. An investor is defined as increasing their position if they hold a greater fraction of the firm's shares at the end of the quarter than they held at the beginning. An institution is defined as increasing their return-adjusted portfolio weight if the security's weight in the investor's portfolio at the end of the quarter is larger than what it would be if the manager did not rebalance their beginning-of-quarter portfolio. We then estimate 58 quarterly cross-sectional regressions of each measure on their lag value and lag quarterly return. To allow direct comparison between the coefficients associated with the independent variables, we standardized (i.e., rescale to zero mean, unit variance) all data each quarter. The average (standardized) coefficients from the 58 cross-sectional regressions and associated t-statistics (computed from time-series standard errors) are reported in panel A. Panels B, C, and D report the averages when limiting the sample to securities with at least 5, 10, or 20 institutional traders, respectively. **Indicates statistical significance at the 1% level; *indicates statistical significance at the 5% level.

Average coefficients from the 58 regressions and associated t-statistics (computed from time-series standard errors) are reported in Table 4. In addition, we repeat the analysis for the standardized fraction of institutions increasing return-adjusted portfolio weights. Results for the sample that includes all securities with at least 1, 5, 10, or 20 institutional trader(s) are reported in panels A–D, respectively.

Consistent with earlier work, institutional investors, as a group, engage in momentum trading. For example, in the regression of the standardized fraction of institutions buying for the sample including all securities with at least one trader (the first regression in panel A), the coefficient associated with lag standardized returns averages 0.0691 (statistically significant at the 1% level). Because the data are standardized, this suggests that a one standard deviation increase in last quarter's return is associated with a 6.91% standard deviation greater fraction of institutions buying this quarter. Institutional momentum trading, however, accounts for little of the institutional herding. That is, adding a standardized lag return to the regression has little impact on the average coefficient associated with last quarter's fraction of institutions buying, for example, the average coefficient reported in the first row of panel A moves from 0.1194 in Table 2 to 0.1133 in Table 4. Because all variables are standardized, the coefficients associated with the lag fraction of institutions buying and lag return are directly comparable—the average coefficient associated with the lag fraction of institutions buying is approximately 64% larger than the average coefficient associated with lag return. Thus, on average, a one standard deviation change in lag institutional demand predicts a 64% greater change in next quarter's institutional demand than a one standard deviation change in lag return. A paired t-test of the hypothesis that the coefficients are equal is rejected at the 1% level (t-statistic = 3.61).

Repeating the analysis for the standardized fraction of institutions increasing return-adjusted portfolio weights (the second regression) yields similar results. In addition, we find similar results for the analysis restricted to securities with at least 5, 10, or 20 institutional traders (panels B–D). In sum, the fraction of institutions increasing their position or return-adjusted portfolio weights is positively related to lag returns as well as their own lag values.

There are two important results to emphasize in Table 4. First, the relation between institutional demand this quarter and last quarter changes little after accounting for momentum trading (i.e., the coefficients associated with lag institutional demand reported in Tables 2–4 are similar). Thus momentum trading does not appear to be the primary source of institutional herding. Second, although there is substantial evidence that institutional investors engage in momentum trading [e.g., Grinblatt, Titman, and Wermers (1995), Jones, Lee, and Weis (1999), Nofsinger and Sias (1999), Wermers (1999, 2000), Cai, Kaul, and Zheng (2000), Sias, Starks, and Titman (2002)], the institutions' demand is much more strongly related to their own lag demand than lag returns.[30]

[30] We can reject the hypothesis (at the 5% level or better) that the average coefficient associated with lag standardized institutional demand equals the average coefficient associated with lag standardized return for each of the eight regressions summarized in Table 4.

3.3 Institutional demand and subsequent returns

Recent work [e.g., Grinblatt and Titman (1989, 1993), Grinblatt, Titman, and Wermers (1995), Jones, Lee, and Weis (1999), Nofsinger and Sias (1999), Wermers (1999, 2000), Sias, Starks, and Titman (2002), Parrino, Sias, and Starks (2003)] documents a positive relation between measures of institutional demand and returns the same and previous quarters. Moreover, these studies suggest that institutional demand is weakly positively correlated with future returns. Assuming institutional herding impacts security returns, the fads, reputational herding, and characteristic herding models suggest that subsequent returns should be inversely related to institutional demand.[31] That is, if price movements result from something other than information, we expect to observe subsequent return reversals. Thus existing evidence is inconsistent with the hypothesis that institutional herding is primarily motivated by agency problems, attraction to security characteristics, or fads.

Because our data and measures differ from the data and measures used in previous studies, we also evaluate the relation between institutional demand and returns. Specifically, each quarter we measure the cross-sectional (across K securities) correlation between the fraction of institutions buying [Equation (1)] and returns measured over the previous quarter, same quarter, following quarter, following six months, and following year.[32] The time-series average of these correlations and associated t-statistics (computed from time-series standard errors) are reported in Table 5.

Consistent with previous studies, we find institutional demand is positively correlated with both current- and prior-quarter returns. Specifically the correlation between the fraction of institutions buying in the current quarter and returns the same (previous) quarter is 7.84% (7.44%). Restricting the sample to securities with at least 5, 10, or 20 institutional traders (Rows 2–4 in Table 5) reveals even stronger relations between the fraction of institutions buying and returns the same and previous quarters. Most important, consistent with previous work, we document a weak positive correlation between the fraction of institutions buying and returns in the following quarter or six months. For the sample including all firms, the evidence suggests the fraction of institutions buying and returns over the following year are nearly independent. However, when restricting the sample to firms with at least 5, 10, or 20 institutional traders, we document stronger positive relations between the fraction of

[31] See Chakravarty (2001), Dennis and Weston (2000), and Sias, Starks, and Titman (2002) for evidence of price effects associated with institutional demand.

[32] Because standardization is a linear rescaling, these are also the correlations between the standardized fraction of institutions buying and returns.

Table 5
Correlation between institutional demand and returns

Sample	Previous quarter return	Same quarter return	Following quarter return	Following 6-month return	Following 12-month return
≥1 Institutional trader	0.0744	0.0784	0.0077	0.0060	− 0.0009
	(14.45)**	(16.94)**	(1.96)	(1.33)	(− 0.25)
≥5 Institutional traders	0.1116	0.1466	0.0221	0.0241	0.0139
	(17.10)**	(22.31)**	(4.36)**	(4.71)**	(3.52)**
≥10 Institutional traders	0.1101	0.1773	0.0291	0.0326	0.0219
	(14.12)**	(25.68)**	(5.17)**	(5.79)**	(4.25)**
≥20 Institutional traders	0.0998	0.2079	0.0257	0.0300	0.0205
	(12.17)**	(28.47)**	(3.47)**	(4.33)**	(3.43)**

For each security and quarter between March 1983 and December 1997 we calculate the fraction of institutional traders that increase their position in the security. An investor is defined as increasing their position if they hold a greater fraction of the firm's shares at the end of the quarter than they held at the beginning. Each quarter, we then calculate the cross-sectional correlation between the fraction of institutions buying and returns over the previous quarter, the same quarter, the following quarter, the following six months, and the following year. The time-series averages of these cross-sectional correlations and associated t-statistics (computed from time-series standard errors) are reported for the sample that includes all securities with at least one institutional trader and samples limited to securities with at least 5, 10, or 20 institutional traders. **Indicates statistical significance at the 1% level; *indicates statistical significance at the 5% level.

institutions buying and returns over the following quarter, six months, or year (all are statistically significant at the 1% level).

The results reported in Table 5 are inconsistent with the joint hypothesis that institutional demand impacts security prices [Dennis and Weston (2000), Chakravarty (2001), Sias, Starks, and Titman (2002)], institutional herding is driven by fads, reputational herding, or characteristic herding, and that the impact of such noninformational herding is reversed within the following year. The results, however, are consistent with models of information-based herding—informational cascades and investigative herding.

3.4 Herding by firm size

The lack of subsequent return reversals is consistent with the hypothesis that institutional herding reflects the manner in which information is impounded into security prices. Thus the results are most consistent with informational cascades (i.e., institutional investors infer information from the trades of other institutions) and investigative herding (i.e., signals are positively correlated across institutional investors). Wermers (1999) posits that informational cascades are more likely in small-capitalization securities because institutional investors would put a relatively larger weight on what the herd is doing and less weight on their own noisy private information. Similarly we hypothesize that the cross-sectional correlation between signals (possibly resulting from following the same indicators) is likely to be stronger in larger stocks with less noisy signals. Thus if institutional herding primarily arises from inferring information from each other's trades (informational cascades), herding should be strongest in small-capitalization securities. Alternatively, if institutional herding primarily arises from correlated signals (investigative herding), herding should be strongest in large-capitalization securities.

The analysis by firm size is complicated by the fact that there are typically many more institutions trading in a large-capitalization security than there are trading in a small-capitalization security. This pattern will affect both the decomposition of the correlation coefficient [i.e., the relative importance of the two terms in Equation (4)] and the cross-sectional correlation between the fraction of institutional investors buying this quarter and the fraction buying last quarter. It affects the decomposition because the number of "herding" terms increases much faster than the number of "following-their-own-trades" terms as the number of investors increases.[33] It affects the correlation because as the number of traders increases, the cross-sectional standard deviation of the fraction of institutions buying tends to fall.[34]

Despite these limitations, we begin by examining the cross-sectional correlation between the fraction of institutions buying this quarter and the fraction buying last quarter for firms within each capitalization quintile to ensure there is evidence of herding and following their own trades within each capitalization quintile. Because our focus is on understanding what drives herding, we limit the sample to securities with at least five institutional traders.[35] Specifically, at the beginning of each quarter we sort all securities with at least five institutional traders into five groups based on beginning-of-quarter capitalization. To allow direct comparison of regression coefficients across capitalization quintiles, we standardize (within each capitalization quintile, each quarter) both the dependent and independent variables to have zero mean and unit variance. Next, we

[33] Specifically, for each firm there are approximately $N_{k,t}$ "following-their-own-trades" terms [i.e., the first term in Equation (4)], $N^*_{k,t}(N_{k,t-1}-1)$ herding terms [i.e., the second term in Equation (4)], and $N^*_{k,t}N_{k,t-1}$ total terms. This holds exactly if every trader who trades in the first period (for firm k) trades in the second period. If an investor trades in only one period, then that trader has no following-their-own-trades term but still participates in the calculation of the herding term. Thus, as the number of traders ($N_{k,t}$) increases, the fraction of total terms accounted for by following-their-own-trades terms declines and the fraction of total terms accounted for by herding terms increases.

[34] Because the distribution of the fraction of institutions buying is smaller for larger firms, a given level of herding or following their own trades will be able to explain a larger portion of next quarter's fraction of institutions buying. In other words, the denominator in the calculation of the correlation is inversely related to capitalization. If small firms often have one or two traders, these firms will often have 100% of traders buying or 100% of traders selling. Alternatively, if a large firm has 50 institutional traders, it is unlikely 100% of those traders will be on one side of the trade. Empirically we document a monotonic inverse relation between the cross-sectional standard deviation of the fraction of institutions buying and capitalization quintile.

[35] Evidence of herding is strongest when securities with few institutional traders are excluded from the analysis (see Table 2). We find similar results, however, for the analysis that includes all securities with at least one institutional trader.

estimate the regression given in Equation (3) and the decomposition given in Equation (4), each quarter, limiting the sample to firms within a given capitalization quintile. The time-series average of the standardized regression coefficients (or equivalently, the correlations), their components, and associated t-statistics (computed from time-series standard errors) are reported in panel A of Table 6 for firms within each capitalization quintile.

The first column reveals that the fraction of institutions buying this quarter is positively correlated with the fraction of institutions buying last quarter for every capitalization quintile (statistically significant at the 1% level for each capitalization quintile). The second and third columns partition the correlation (or, equivalently, the slope coefficient) for firms within each capitalization quintile into the portion that results from institutional investors following their own trades and the portion that results from institutional investors following other institutional investors' trades. The results reveal statistically significant (at the 1% level) evidence of both herding and following their own trades in every capitalization quintile. Not surprisingly, given the above discussion, the relative contribution of herding (following their own trades) is larger (smaller) in large-capitalization securities.

As discussed above, both the magnitude and the decomposition of the correlation are influenced by the number of institutional traders. Thus, although the results in panel A of Table 6 reveal institutional demand can better explain subsequent institutional demand (i.e., the correlation is stronger) for stocks in the top capitalization quintile than stocks in the middle three capitalization quintiles, the results do not necessarily suggest institutions exhibit greater herding in large-capitalization stocks. Therefore we next examine measures of following their own trades and following each other's trades that are independent of the number of institutions trading. Specifically, we compute the average "following-their-own-trades" contribution for each security-quarter as the numerator of the first term on the right-hand side of Equation (4) restricted to security k divided by the number of terms used in the first term on the right-hand side of Equation (4) for security k in quarter t:

$$\begin{aligned} &Average\ following\text{-}their\text{-}own\text{-}trades\ contribution_{k,t} \\ &= \sum_{n=1}^{N^*_{k,t}} \frac{\left(D_{n,k,t} - \overline{Raw\Delta_t}\right)\left(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{N^*_{k,t}}, \end{aligned} \tag{9}$$

where $N^*_{k,t}$ is the number of managers trading security k in both quarter $t-1$ and quarter t. Similarly we compute the average "herding" contribution for each security-quarter as the numerator of the second term on the right-hand side of Equation (4) restricted to security k divided

Table 6
Herding and following their own trades by capitalization quintile (≥5 institutional traders)

Panel A: Coefficient and slope decomposition

Capitalization quintile	Average coefficient (β)	Partitioned slope coefficient: Institutions following their own trades	Partitioned slope coefficient: Institutions following others' trades	Average R^2
Small firms	0.1801	0.0892	0.0909	3.65%
	(21.17)**	(15.05)**	(11.13)**	
Quintile 2	0.1469	0.0743	0.0726	2.53%
	(18.30)**	(16.23)**	(10.06)**	
Quintile 3	0.1307	0.0618	0.0690	1.95%
	(20.22)**	(17.43)**	(13.31)**	
Quintile 4	0.1368	0.0409	0.0959	2.20%
	(17.94)**	(15.36)**	(13.58)**	
Large firms	0.1644	0.0269	0.1375	3.07%
	(20.60)**	(20.17)**	(17.98)**	

Panel B: Average contributions

	Average contribution from following their own trades	Average contribution from following others' trades
Small firms	0.0439	0.0036
	(16.91)**	(10.40)**
Quintile 2	0.0372	0.0020
	(18.86)**	(9.94)**
Quintile 3	0.0340	0.0014
	(19.79)**	(12.36)**
Quintile 4	0.0285	0.0013
	(22.61)**	(12.77)**
Large firms	0.0255	0.0001
	(27.44)**	(17.15)**
F-statistic (p-value)	16.33	28.97
	(0.01)	(0.01)

For each security and quarter between March 1983 and December 1997 we calculate the fraction of institutional traders that increase their position in the security. An investor is defined as increasing their position if they hold a greater fraction of the firm's shares at the end of the quarter than they held at the beginning. Firms (with at least five institutional traders) are then sorted, each quarter, into quintiles based on beginning of quarter capitalization. Within each capitalization quintile, all data are standardized (i.e., rescaled to zero mean, unit variance) each quarter. We then estimate 58 quarterly cross-sectional regressions of the fraction of institutional traders buying on the lag fraction of institutional traders buying for firms within each capitalization quintile. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between the fraction of institutional traders buying this quarter and the fraction of institutional traders buying last quarter. The first column in panel A reports the time-series average of these 58 correlation coefficients and associated t-statistic (in parentheses, computed from time-series standard errors). The second and third columns in panel A report the portion of the correlation [see Equation (4)] that results from institutional investors following their own lag trades and the portion that results from institutions following the previous trades of other institutions (herding). We then compute the cross-sectional average contribution from following their own trades [Equation (9)] and following others' trades [Equation (10)] for firms within each capitalization quintile, each quarter. Time-series averages and associated t-statistics (computed from time-series standard errors) of these 58 cross-sectional averages are reported in panel B. The last row in panel B reports F-statistics associated with the null hypothesis that the values are equal across capitalization quintiles. **Indicates statistical significance at the 1% level; *indicates statistical significance at the 5% level.

by the total number of terms used in the second term on the right-hand side of Equation (4) for security k in quarter t:

$$\text{Average herding contribution}_{k,t} = \sum_{n=1}^{N_{k,t}} \sum_{m=1,m\neq n}^{N^*_{k,t-1}} \frac{\left(D_{n,k,t} - \overline{Raw\Delta_t}\right)\left(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{N_{k,t}N^*_{k,t-1}}, \tag{10}$$

where $N_{k,t}$ is the number of managers trading security k in quarter t and $N^*_{k,t-1}$ is the number of *different* managers trading security k in quarter $t-1$. Equations (9) and (10) measure the *average* contribution to the correlation of following their own trades and following each other's trades, respectively, for each firm. The number of traders or the cross--sectional standard deviation of the fraction of institutions buying, therefore, do not affect these measures.

Equations (9) and (10) are estimated for each security-quarter with at least five institutional traders. We then compute the cross-sectional average across securities in each capitalization quintile each quarter. Table 6 (panel B) reports the time-series average of the 58 cross-sectional averages and associated t-statistics (computed from time-series standard errors) for securities within each capitalization quintile. In addition, the last row in panel B reports F-statistics associated with the null hypothesis that the estimates are equal across capitalization quintiles.[36]

Consistent with panel A, the results in the first column of panel B reveal strong evidence of following their own trades for every capitalization quintile. Moreover, we document a monotonic inverse relation between the average following-their-own-trades contribution and capitalization. The F-statistic reveals that we can reject the hypothesis (at the 1 % level) that the average following-their-own-trades contribution is equal across capitalization quintiles. The second column in panel B reveals the average herding contribution is positive and statistically differs from zero (at the 1% level or better) for every capitalization quintile. In addition, we document a monotonic inverse relation between the average herding contribution and capitalization. Institutional investors' trades this quarter are more likely to follow other institutions' trades last quarter in smaller capitalization securities. The F-statistic reveals that we can reject the hypothesis (at the 1% level) that the average herding contribution is equal across capitalization quintiles.

The difference between the average contribution from following their own trades and the average contribution from following others' trades suggests that a given institutional investor is much more likely to follow

[36] These F-statistics are computed from the 290 cross-sectional averages (5 capitalization quintiles * 58 quarters).

their own lag trade than the lag trade of another institutional investor. The results suggest that institutional investors accumulate and dispose of positions over time through multiple orders. Although the results are not well explained by the empirical evidence on the execution of a given order [Keim and Madhavan (1995, 1997), Chan and Lakonishok (1995)], the pattern across firm size is consistent with the hypothesis that the tendency to follow their own trades is related to trading costs.[37,38] These trading costs include both a liquidity component [e.g., Grossman and Miller (1988)] and an informed trading component [e.g., Kyle (1985)]. Institutional investors may build a position over time because they fear that the liquidity premium associated with a single large order or even a series of orders within a quarter would be too great. Similarly institutions may build or dispose of positions over time because they fear that a single order or a series of orders within a quarter would impact the price by the (real or perceived) informational content of the order flow imbalance. Moreover, both of these costs are likely to be higher for less liquid, smaller capitalization securities.

Taking longer to accumulate a position will reduce the liquidity premium paid by the investor. The effect on the informed trading cost, however, is less clear. Although building the position over more than one quarter will force the investor to reveal their interest (through the 13F filing), this may be a weaker signal than that given by the order flow imbalance if the investor tried to establish or liquidate a large position within a given quarter. That is, market participants likely infer information from both the change in position (revealed by the 13F filing) and the demand for immediacy associated with that change (revealed by the order flow imbalance).[39]

In sum, the results reveal evidence of herding and following their own trades in every capitalization quintile. In addition, the results reveal that institutional investors are more likely to follow their own prior quarter trades in smaller securities consistent with the hypothesis that institutions following their own lag trades is related to trading costs. Most important,

[37] Keim and Madhavan (1995, 1997) and Chan and Lakonishok (1995) find evidence that many institutional investor orders are executed over multiple days. Given the evidence that individual orders are usually fully executed within a day or two, however, it seems unlikely that executing a given order over several days would explain why institutional investors tend to follow their own last-quarter transactions. That is, the results are unlikely to reflect the gradual execution of single orders, but more likely reflect institutional investors issuing multiple orders for the same security over time.

[38] It is also possible that institutional investors follow their own trades as a result of habit investing, that is, time-series correlation in their net flows and investing (divesting) those flows in (from) their existing portfolio. This interpretation, however, is inconsistent with the analysis of changes in portfolio weights. Moreover, the habit-investing explanation suggests the pattern should not be related to capitalization.

[39] For example, a recent *Wall Street Journal* article [Lucchetti and Angwin (2002)] noted, "Since last March, Janus has sold about 25% of its 245 million-share position in AOL, and last week, the firm disclosed in regulatory filings that it had *accelerated* (emphasis added) its selling during the fourth quarter, disposing of an additional 32 million shares."

institutional investors are more likely to herd in smaller capitalization securities. Assuming informational cascades are more likely in small-capitalization securities and investigative herding is more likely in large-capitalization securities, the results suggest institutional herding primarily results from institutions inferring information from each other's trades. Given the lack of return reversals, however, our analysis suggests these informational cascades are rational.

4. Changes Over Time

The number of institutional investors filing 13F reports increases from 556 in December 1983 to 1274 in December 1997. It is not clear, however, how increased institutionalization should affect herding. If the number of institutions doubles by duplicating each of the existing institutional investors and therefore the fraction of institutions buying does not change, the correlation between the fraction of institutional buyers this quarter and last quarter does not change. Nonetheless, several factors lead one to suspect herding may change over time. First, the environment faced by institutional investors is dynamic [Bennett, Sias, and Starks (2003)], suggesting the incentives to herd may vary over time. Second, the growth in institutional ownership is not uniform across investor types. Thus the analysis over time reflects a decline in the relative importance of bank trust departments and an increase in the relative importance of independent investment advisors (see Table 1). Third, market characteristics change considerably over time. For example, markets experienced substantial increases in share turnover and firm-specific risk over the past two decades [Campbell et al. (2001), Chordia, Roll, and Subrahmanyam (2001)]. Fourth, the number of securities traded by institutional investors increases over time.

We begin the analysis of changes over time by dividing the sample into two 29-quarter periods (September 1983 to September 1990 and December 1990 to December 1997) and comparing the distributions of standardized coefficients (and the decomposed coefficients) computed from the cross-sectional regressions for the entire sample of firms as well as for subsamples of firms within each capitalization quintile. As before, we limit the sample to securities with at least five institutional traders. Panel A of Table 7 reports the mean correlations over each subperiod and a t-statistic associated with the null hypothesis that the time-series mean in the first period equals the time-series mean in the second period. The results reveal that we can reject the hypothesis that the correlation is equal in both periods for the sample as a whole and for the middle three capitalization quintiles. The decomposition reveals that this primarily results from a decline in the portion attributed to institutional investors following their own lag trades.

Table 7
Analysis over time (≥5 institutional traders)

Panel A: Coefficient and slope decomposition

		Partitioned slope coefficient	
Sample	Average coefficient (β_t)	Institutions following their own trades	Institutions following others' trades
All firms (198309–199009)	0.1982	0.0823	0.1158
All firms (199012–199712)	0.1527	0.0524	0.1003
t-statistic	3.65**	4.57**	1.37
Small firms (198309–199009)	0.1933	0.1058	0.0857
Small firms (199012–199712)	0.1668	0.0708	0.0960
t-statistic	1.58	3.38**	−0.63
Quintile 2 (198309–199009)	0.1683	0.0932	0.0751
Quintile 2 (199012–199712)	0.1255	0.0553	0.0702
t-statistic	2.83**	4.91**	0.34
Quintile 3 (198309–199009)	0.1456	0.0777	0.0679
Quintile 3 (199012–199712)	0.1159	0.0458	0.0700
t-statistic	2.39*	5.55**	−0.20
Quintile 4 (198309–199009)	0.1682	0.0508	0.1175
Quintile 4 (199012–199712)	0.1055	0.0301	0.0744
t-statistic	4.86**	4.20**	3.30**
Large firms (198309–199009)	0.1707	0.0269	0.1438
Large firms (199012–199712)	0.1581	0.0270	0.1312
t-statistic	0.79	−0.02	0.82

Panel B: Average contributions

	Average contribution from following their own trades	Average contribution from following others' trades
All firms (198309–199009)	0.0401	0.0028
All firms (199012–199712)	0.0284	0.0021
t-statistic	4.60**	2.26**
Small firms (198309–199009)	0.0523	0.0035
Small firms (199012–199712)	0.0355	0.0037
t-statistic	3.57**	−0.30
Quintile 2 (198309–199009)	0.0456	0.0022
Quintile 2 (199012–199712)	0.0287	0.0018
t-statistic	5.16**	0.90
Quintile 3 (198309–199009)	0.0421	0.0015
Quintile 3 (199012–199712)	0.0259	0.0013
t-statistic	5.95**	0.80
Quintile 4 (198309–199009)	0.0321	0.0017
Quintile 4 (199012–199712)	0.0249	0.0010
t-statistic	3.08**	4.12**
Large firms (198309–199009)	0.0242	0.0011
Large firms (199012–199712)	0.0269	0.0009
t-statistic	−1.43	2.31*

For each security and quarter between March 1983 and December 1997 we calculate the fraction of institutional traders that increase their position in the security. Firms (with at least five institutional traders) are then sorted, each quarter, into quintiles based on beginning of quarter capitalization. Within each capitalization quintile, all data are standardized (i.e., rescaled to zero mean, unit variance) each quarter. We then estimate 58 quarterly cross-sectional regressions of the fraction of institutional traders buying on the lag fraction of institutional traders buying for firms within each capitalization quintile. We also repeat the analysis for the sample including all firms (with at least five institutional traders). Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between the fraction of institutional traders buying this quarter and the fraction of institutional traders buying last quarter. Panel A reports the time-series average of these correlation coefficients and the portion of the correlation [see Equation (4)] that results from institutional investors following their own lag trades and the portion that results from institutions following the previous trades of other institutions (herding) over the first 29 quarters in the sample period (198309–199009) and the second 29 quarters in the sample period (199012–199712). The third row reports *t*-statistics from a difference in means test of the hypothesis that the mean value in the first period equals the mean value in the second period. Panel B repeats the analysis for the average contribution from following their own trades [Equation (9)] and following others' trades [equation (10)] for firms within each capitalization quintile and the sample including all firms (with at least five institutional traders). **Indicates statistical significance at the 1% level; *indicates statistical significance at the 5% level.

Similar to the analysis by firm size, however, comparison of the average coefficient across periods does not allow us to infer changes in the propensity to herd or follow their own lag trades over time.[40] Thus, to allow direct comparison across time we compute the average following-their-own-trades contribution and average herding contribution [Equations (9) and (10), respectively] for each stock-quarter. We then compute the cross-sectional average of these contributions each quarter and report (in panel B of Table 7) the time-series average of these cross-sectional averages over each subperiod. The third row reports a *t*-statistic (from a difference in means test) associated with the null hypothesis that the time-series mean in the first period equals the time-series mean in the second period.

The results reveal that institutional investors have become less likely to follow their own and other institutional investors' trades over time (i.e., the differences in means across periods for both contribution measures are statistically significant at the 1% level). Evaluation across capitalization quintiles reveals that the decline in the average following-their-own-trades contribution is statistically significant in all but the largest capitalization quintile. The decline in the propensity to follow their own trades is consistent with the hypothesis that increases in market liquidity over time [Chordia, Roll, and Subrahmanyam (2001)] have increased the speed with which institutional investors are willing to enter and exit positions. This interpretation is also consistent with the hypothesis that institutions' tendency to follow their own trades is related to trading costs (see Section 3.4). Alternatively, the decline in herding is primarily driven by the largest stocks. We find no evidence of meaningful declines in the average herding contribution for the bottom three capitalization quintiles. Assuming institutional herding is primarily driven by informational cascades (see Section 3.4), the results suggest that institutional investors' tendency to infer information from each other's trades has declined in large-capitalization stocks over time. This may have resulted from increased efficiency in large-capitalization stocks. That is, if information is impounded faster in large capitalization stocks in the more recent period, institutional investors will infer less information from each other's previous-quarter's trades.

5. Herding by Investor Type

Previous studies of herding behavior focus on pension funds [Lakonishok, Shleifer, and Vishny (1992)] or mutual funds [Grinblatt, Titman, and

[40] Comparison of correlations across time is clouded because the number of traders is not constant over time. Thus both the correlation and the decomposition will be affected (see Section 3.4 for additional detail).

Wermers (1995), Wermers (1999)]. Previous work [Del Guercio (1996), Bennett, Sias, and Starks (2003)] also documents important differences in the environments faced by different types of institutional investors (e.g., regulatory requirements, holding periods, competition) that may, in turn, influence the likelihood these investors herd and whether herding is only within classifications or if some types of institutions lead other types of institutions. Our data provide a unique opportunity to examine these issues.

Examination of herding by investor type also provides further tests of the reputational and characteristic herding explanations. If institutional herding is driven by institutions favoring stocks with the same characteristics and those preferences differ across institutional classes [Del Guercio (1996), Bennett, Sias, and Starks (2003)], then institutions should be more likely to follow similar-type institutions than different types of institutions. Moreover, if institutional herding is driven by reputational concerns, then institutional investors should also be more likely to follow similar-type institutions than different types of institutions, for example, independent investment advisors should be more likely to follow other independent investment advisors with whom they directly compete than bank trust departments, insurance companies, mutual funds, or unclassified investors. In addition, we hypothesize that mutual funds and independent investment advisors are most likely to experience changes in their net flows resulting from changes in their reputations.[41] Thus the reputational herding explanation suggests mutual funds and independent investment advisors should exhibit the strongest tendency to herd.

We begin the analysis by computing the standardized fraction of bank trust departments trading each security that are buyers, each quarter. We then regress the standardized fraction of bank trust departments buying this quarter (denoted $\Delta^b_{k,t}$) on the standardized fraction of institutional investors (all classifications) buying last quarter and limit the sample to securities that have at least five bank trust departments trading this quarter and at least five institutional investors trading last quarter:

$$\Delta^b_{k,t} = \beta^b_t \Delta_{k,t-1} + \varepsilon_{k,t}. \tag{11}$$

We then repeat the analysis, replacing the dependent variable with each of the other types of institutional investors. The time-series average of these

[41] Unclassified institutional investors (which primarily consist of foundations, endowments, ESOPs, and internally managed pension funds) and insurance companies are less likely to experience changes in net flows resulting from changes in their reputations. One could argue that bank trust departments could also be subject to such patterns (e.g., bank trust departments with strong recent performance might experience net inflows while those with poor recent performance might experience net outflows). Nonetheless, we maintain that given the more conservative nature of investors utilizing bank trust departments [Del Guercio (1996), Bennett, Sias, and Starks (2003)], bank trust departments are less likely to experience these patterns than mutual funds or independent investment advisors.

58 standardized regression coefficients (or equivalently, correlation coefficients) are reported in the first column in panel A of Table 8 (t-statistics, reported in parentheses, are based on time-series standard errors). The results reveal a statistically significant (at the 1% level) positive relation between the fraction of traders buying in each classification and the lag aggregate fraction of traders buying.

As before, the fraction of buyers for a given institutional investor class may be related to the lag fraction of aggregate institutional buyers for one of two reasons—individual institutional investors following their own lag trades or institutional investors following the lag trades of other institutional investors. Moreover, the second term can be further decomposed into two components—following other traders of the same institutional classification or following traders that are members of a different institutional class. In the case of bank trust departments, for example, the correlation can be decomposed as (see the proof in the appendix):

$$\begin{aligned}
\beta_t^b = \rho(\Delta_{k,t}^b, \Delta_{k,t-1}) = & \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t}^b)\sigma(Raw\Delta_{k,t-1})}\right] \\
& \times \sum_{k=1}^{K}\left[\sum_{b=1}^{B_{k,t}} \frac{\left(D_{b,k,t} - \overline{Raw\Delta_t^b}\right)\left(D_{b,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{B_{k,t}N_{k,t-1}}\right] \\
& + \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t}^b)\sigma(Raw\Delta_{k,t-1})}\right] \\
& \times \sum_{k=1}^{K}\left[\sum_{b=1}^{B_{k,t}} \sum_{m=1,m\neq b,m\in B}^{B_{k,t-1}} \frac{\left(D_{b,k,t} - \overline{Raw\Delta_t^b}\right)\left(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{B_{k,t}N_{k,t-1}}\right] \\
& + \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t}^b)\sigma(Raw\Delta_{k,t-1})}\right] \\
& \times \sum_{k=1}^{K}\left[\sum_{b=1}^{B_{k,t}} \sum_{m=1,m\notin B}^{N_{k,t-1}-B_{k,t-1}} \frac{\left(D_{b,k,t} - \overline{Raw\Delta_t^b}\right)\left(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{B_{k,t}N_{k,t-1}}\right],
\end{aligned} \tag{12}$$

where $D_{b,k,t}$ is a dummy variable that equals one (zero) if bank trust department b is a buyer (seller) of security k in quarter t and $B_{k,t}$ is the number of bank trust departments trading stock k in quarter t. $B_{k,t-1}$ is similarly defined for quarter $t-1$. $N_{k,t-1}-B_{k,t-1}$ is the number of non-bank trust department institutional investors trading stock k in quarter $t-1$. The first term in Equation (12) is the portion of the correlation attributed to bank trust departments following their own lag trades. The second term is the portion of the correlation attributed to bank

Table 8
Analysis by investor type (≥5 institutional traders)

Panel A: Coefficient and slope decomposition

		Partitioned slope coefficient				
			Institutions following others' trades			
Trader type	Average coefficient (β)	Following their own trades	All	Same type	Different type	Average R^2
Banks	0.1293	0.0207	0.1086	0.0499	0.0587	1.92%
	(19.55)**	(8.15)**	(18.94)**	(15.25)**	(15.61)**	
Insurance companies	0.0495	0.0164	0.0331	0.0047	0.0284	0.45%
	(8.29)**	(5.75)**	(4.84)**	(4.23)**	(4.42)**	
Mutual funds	0.0521	0.0134	0.0387	0.0029	0.0358	0.57%
	(7.14)**	(8.69)**	(5.56)**	(2.35)*	(5.54)**	
Independent advisors	0.1338	0.0587	0.0750	0.0344	0.0407	1.98%
	(23.01)**	(26.03)**	(13.24)**	(11.55)**	(10.86)**	
Unclassified	0.0469	0.0081	0.0388	0.0068	0.0320	0.66%
	(5.32)**	(4.85)**	(4.36)**	(3.42)**	(3.90)**	

Panel B: Average contributions

	Average contribution from following their own trades	Average contribution from following others' trades	Average contribution from following same type traders	Average contribution from following different type traders	Average "same contribution" less average "different contribution"
Banks	0.0200	0.0023	0.0033	0.0018	0.0015
	(11.97)**	(18.44)**	(14.06)**	(14.37)**	(6.66)**
Insurance companies	0.0248	0.0006	0.0012	0.0006	0.0006
	(13.18)**	(5.99)**	(5.46)**	(5.33)**	(3.06)**
Mutual funds	0.0347	0.0006	0.0009	0.0006	0.0002
	(22.05)**	(5.11)**	(2.83)**	(4.98)**	(0.81)
Independent advisors	0.0367	0.0016	0.0016	0.0017	−0.0001
	(28.13)**	(12.51)**	(11.40)**	(10.43)**	(−0.38)
Unclassified	0.0410	0.0017	0.0015	0.0019	−0.0005
	(25.10)**	(8.99)**	(7.48)**	(8.57)**	(−2.35)*
F-statistic	25.71	34.96	17.49	22.05	
(p-value)	(0.01)	(0.01)	(0.01)	(0.01)	

For each security and quarter between March 1983 and December 1997 we calculate the fraction of institutional traders overall and by each investor type (bank trust departments, insurance companies, mutual funds, independent investment advisors, and unclassified institutional investors) that increase their position in the security. We then restrict the sample to securities with at least five bank trust departments trading this quarter and five institutional investors (of any classification) trading last quarter and estimate 58 quarterly cross-sectional regressions of the fraction of bank trust department traders buying on the lag fraction of all institutional traders buying. Because there is a single independent variable in each regression and the data are standardized, these regression coefficients are also the cross-sectional correlations between the fraction of bank trust department traders buying this quarter and the fraction of all institutional traders buying last quarter. The first column in panel A reports the time-series average of these 58 correlation coefficients and associated t-statistic (in parentheses, computed from time-series standard errors). The second and third columns report the portion of the correlation [see Equation (4)] that results from bank trust departments following their own lag trades and the portion that results from bank trust departments following the previous trades of other institutions (herding). The fourth and fifth columns report the portion of the coefficient that results from bank trust departments following other bank trust department trades and the portion that results from bank trust departments following non-bank trust department trades, respectively [see Equation (12)]. The analysis is then repeated for each of the other four institutional classifications. Panel B repeats the analysis for the average contribution from following their own trades [Equation (9)], following others' trades [Equation (10)], following similarly classified traders [Equation (13)], and following differently classified traders [Equation (14)]. The last column in Panel B reports the average difference between columns three and four (and associated t-statistic computed from a paired t-test). The last row in panel B reports F-statistics associated with the null hypothesis that values are equal across investor classifications. **Indicates statistical significance at the 1% level; *indicates statistical significance at the 5% level.

trust departments following other bank trust departments. The last term is the portion of the correlation attributed to bank trust departments following other non-bank trust department institutions.

The second through fifth columns in panel A of Table 8 report the time-series average decomposition of each of the four components for each of the five types of institutional investors (t-statistics are computed from time-series standard errors). The results reveal statistically significant evidence (at the 1% level) of following their own trades (second column) and following other institutional investors trades (third column) for every institutional classification. Moreover, both components of the second term—following the same-type traders (fourth column) and following different-type traders (fifth column)—differ significantly from zero (at the 5% level or better) for every institutional classification.

Comparison of the average coefficient across investor types reveals that lag changes in institutional ownership has the greatest ability to explain cross-sectional variation in subsequent changes in ownership by bank trust departments and independent advisers. Again, however, the comparison of correlations across investor types does not allow us to infer the propensity to herd due to differences in the number of traders within each classification.[42] To allow direct comparison across investor types, we again compute the average following-their-own-trades contribution and average herding contribution for each stock-quarter.[43] In addition, we compute the average herding contribution from bank trust departments following other bank trust departments for each stock-quarter as

$$\textit{Average same-type herding contribution}^{b}_{k,t} = \sum_{b=1}^{B_{k,t}} \sum_{m=1,m\neq b,m\in B}^{B^*_{k,t-1}} \frac{\left(D_{b,k,t} - \overline{Raw\Delta^b_t}\right)\left(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{B_{k,t}B^*_{k,t-1}}, \tag{13}$$

where $B^*_{k,t-1}$ is the number of *different* bank trust departments trading security k in quarter $t-1$. Similarly we compute the average herding contribution from bank trust departments following non-bank trust departments as

$$\textit{Average different-type herding contribution}^{b}_{k,t} = \sum_{b=1}^{B_{k,t}} \sum_{m=1,m\notin B}^{N_{k,t-1}-B_{k,t-1}} \frac{\left(D_{b,k,t} - \overline{Raw\Delta^b_t}\right)\left(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{B_{k,t}\left(N_{k,t-1} - B_{k,t-1}\right)}, \tag{14}$$

[42] As with the comparison across firm size, comparison of correlation across investor types is clouded because the number of traders is not constant across investor types (see Section 3.4 for additional details).

[43] The average following-their-own-trades contribution is equivalent to Equation (9), but limited to bank trust departments (or whichever group is examined). The average herding contribution is equivalent to

where $N_{k,t-1}-B_{k,t-1}$ is the number of non-bank trust department institutions trading security k in quarter $t-1$. Equations (13) and (14) measure the *average* contribution to the correlation of following other bank trust departments and following other types of institutional investors, respectively. Similar to Equations (9) and (10), these measures are not affected by the number of traders nor the cross-sectional standard deviation of institutions buying.

Limiting the sample to securities with at least five bank trust departments trading this quarter and five institutional investors trading last quarter, we compute the quarterly cross-sectional average following-their-own-trades contribution [i.e., analogous to Equation (9)], herding contribution [i.e., analogous to Equation (10)], following same-type herding contribution [Equation (13)], and following different-type herding contribution [Equation (14)]. The time-series averages (and associated t-statistic computed from the time-series standard error) of these cross--sectional averages are reported in the first row in panel B of Table 8. The analysis is then repeated for each of the other types of institutional investors. The last row in Table 8 reports F-statistics associated with the null hypothesis that the estimates are equal across investor types.[44] The last column of panel B reports the time-series average difference between the cross-sectional average contribution from following the same type of traders (third column) and the cross-sectional average contribution from following different types of traders (fourth column). The t-statistic associated with the value in the last column is based on a paired t-test for difference in means.

The results in the last row of Table 8 reveal that we can reject the hypothesis (at the 1% level) of equality across investor types for all four "average contribution" measures. Mutual funds, independent advisors, and unclassified investors more often follow their own lag trades than bank trust departments or insurance companies. Bank trust departments, unclassified investors, and independent advisers more often herd than mutual funds or insurance companies. The results are consistent with the hypothesis that the tendency to herd is influenced by the differing environments faced by these investors.

The last column reveals mixed support for the reputational and characteristic herding hypotheses. Bank trust departments and insurance companies are more likely to follow similar-type institutions than different types of institutions. That is, the average contribution from following same-type traders is greater than the average contribution from following

Equation (10), but the first summation is from $b=1$ to the number of bank trust departments trading security k in quarter t. The second summation still includes all traders (regardless of type) trading security k in period $t-1$.

[44] These F-statistics are computed from the 290 cross-sectional averages (5 investor types * 58 quarters).

different-type traders for these two investor types (statistically significant at the 1% level). Mutual funds, independent investment advisers, and unclassified institutional investors, however, exhibit no such pattern inconsistent with reputational and characteristic herding models. In fact, unclassified institutional investors are more likely to follow differently classified traders than similarly classified traders (statistically significant at the 5% level). The two trader types that should be most concerned about their reputations (mutual funds and independent advisors) exhibit little evidence of focusing on their most direct competitors' trades. In addition, mutual funds exhibit the weakest tendency to herd, inconsistent with the reputational herding hypothesis.

In sum, the results in Table 8 reveal evidence of following their own and others' trades for each institutional classification. Nonetheless, we document substantial variation in herding across investor types—bank trust departments exhibit the strongest propensity to herd and mutual funds and insurance companies exhibit the weakest propensity to herd. In addition, two of the five trader types are more likely to follow similarly classified traders than differently classified traders, consistent with reputational and characteristic herding models. Three of the five trader types fail to exhibit this pattern. The results, however, are also clouded by the 13F reporting process. For example, because 13F reporting is aggregated across different units within an institution, we cannot measure mutual fund herding at the fund level.

6. Conclusion

Despite strong theoretical foundations and the seemingly common perception that professional investors herd, existing studies find little evidence that institutional investors engage in herding behaviors. This study takes a new approach to testing for institutional herding by directly examining the cross-sectional temporal dependence in institutional demand over adjacent quarters. We demonstrate that the fraction of institutions buying this quarter will positively covary with the fraction of institutions buying last quarter if institutional investors follow their own lag trades or if institutional investors follow each other into and out of the same securities (herd).

Our results reveal that the fraction of institutions increasing their position in a security this quarter is strongly related to the fraction increasing their position last quarter. This correlation is equally attributed to institutions following their own last-quarter's trades and institutions following each other's last-quarter's trades. Analysis of changes in portfolio weights reveals institutional investors' tendency to follow their own lag trades does not result from time-series correlation in their net flows and investing net flows in their existing portfolios. Analyses across capitalizations and time suggest that institutional investors' tendency to follow their own lag trades is related to trading costs. Specifically, the results are consistent with the hypothesis that institutional investors accumulate and liquidate positions over time to minimize the price effects associated with their trading.

The analysis of changes in portfolio weights reveals that herding does not primarily result from time-series and cross-sectional correlation in the flows to investors ("habit investing"). Although we find evidence of institutional momentum trading, such trading accounts for little of the herding. Moreover, our results suggest that institutional demand is more strongly related to lag institutional demand than lag returns. We find no evidence that institutional herding drives prices from fundamental values. To the contrary, we find that institutional demand is weakly, but positively, related to returns over the following year, suggesting institutional herding reflects that manner in which information is impounded into securities prices. We also find evidence that herding declines over time (in large stocks) and differs across investor types. Evaluation across capitalizations suggests the results are most consistent with the hypothesis that institutional herding primarily results from institutions inferring information from each other's trades.

Appendix: Proof of Equations (4) and (12)

Equation (2) defines the standardized fraction of institutions buying security k in quarter t as the raw fraction less the cross-sectional average raw fraction in quarter t divided by the cross-sectional standard deviation of the raw fraction of institutions buying in quarter t:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})}, \tag{15}$$

where $Raw\Delta_{k,t}$ is the fraction of institutional traders that buy security k in quarter t. Because $Raw\Delta_{k,t}$ is the sum of the number of institutional investors buying security k this quarter divided by the number of institutional investors trading the security this quarter, the standardized fraction of institutions buying security k in quarter t can be written as

$$\Delta_{k,t} = \frac{\left[\sum_{n=1}^{N_{k,t}} \frac{D_{n,k,t}}{N_{k,t}}\right] - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})}, \tag{16}$$

where $N_{k,t}$ is the number of institutional investors trading security k in quarter t and $D_{n,k,t}$ is a dummy variable that equals one (zero) if institutional investor n buys (sells) security k in quarter t. The slope coefficient in Equation (3) is given as

$$\beta_t = \frac{\operatorname{cov}(\Delta_{k,t},\ \Delta_{k,t-1})}{\sigma^2(\Delta_{k,t-1})} = \frac{\frac{1}{K-1}\sum_{k=1}^{K} \Delta_{k,t}\Delta_{k,t-1}}{\sigma^2(\Delta_{k,t-1})} = \frac{1}{K-1}\sum_{k=1}^{K} \Delta_{k,t}\Delta_{k,t-1}, \tag{17}$$

where K is the number of securities included in the regression. The numerator in Equation (17) is the cross-sectional covariance between the standardized fraction of institutions buying this quarter and last quarter. Because the data are standardized, the denominator ($\sigma^2(\Delta_{k,t-1})$) in Equation (17) is one, that is, the slope coefficient is the covariance between the standardized data. Moreover, because the cross-sectional standard deviation of the current quarter's fraction of institutions buying is also one (i.e., $\sigma(\Delta_{k,t}) = \sigma(\Delta_{k,t-1}) = 1$), the covariance is also equal to the correlation. Thus the slope coefficient from the standardized regression is equal to the correlation. Furthermore, because standardization is simply a linear rescaling of the original data, the correlation between the standardized variables also equals the correlation between the current- and lag-quarter's raw fraction of institutions buying:

$$\beta_t = \rho(\Delta_{k,t},\ \Delta_{k,t-1}) = \rho(Raw\Delta_{k,t},\ Raw\Delta_{k,t-1}). \tag{18}$$

Substituting Equation (16) into the right-hand side of Equation (17), an equivalent expression of this correlation (or slope coefficient) is

$$\beta_t = \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right]\sum_{k=1}^{K}\left[\left(\sum_{n=1}^{N_{k,t}}\frac{D_{n,k,t}-\overline{Raw\Delta_t}}{N_{k,t}}\right)\left(\sum_{n=1}^{N_{k,t-1}}\frac{D_{n,k,t-1}-\overline{Raw\Delta_{t-1}}}{N_{k,t-1}}\right)\right], \tag{19}$$

where $N_{k,t-1}$ is the number of institutional investors trading stock k in quarter $t-1$ and $D_{n,k,t-1}$ is a dummy variable that equals one (zero) if trader n is a buyer (seller) in quarter $t-1$. Using the distributive property of the product of sums, Equation (19) can be written as

$$\begin{aligned}
\beta_t &= \rho(\Delta_{k,t},\ \Delta_{k,t-1}) \\
&= \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right]\sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}}\frac{(D_{n,k,t}-\overline{Raw\Delta_t})(D_{n,k,t-1}-\overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right] \\
&\quad + \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] \\
&\quad \times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}}\sum_{m=1,m\neq n}^{N_{k,t-1}}\frac{(D_{n,k,t}-\overline{Raw\Delta_t})(D_{m,k,t-1}-\overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right].
\end{aligned} \tag{20}$$

The first term on the right-hand side of Equation (20) is the portion of correlation that results from institutional investors following themselves into and out of the same securities, for example, if investor n buys security k in quarters t and $t-1$ or sells security k in both quarters, the first term will be positive. The second term on the right-hand side of Equation (20) is the portion of the correlation that results from institutional investors following each other into and out of the same securities, for example, if investor m buys (sells) security k in quarter $t-1$ and investor n buys (sells) security k in quarter t, the second term will be positive.

Next, define the standardized fraction of bank trust departments buying security k in quarter t as the raw fraction of bank trust departments less the cross-sectional average raw fraction of bank trust departments buying in quarter t divided by the cross-sectional standard deviation of the raw fraction of bank trust departments buying in quarter t:

$$\Delta^b_{k,t} = \frac{Raw\Delta^b_{k,t} - \overline{Raw\Delta^b_t}}{\sigma(Raw\Delta^b_{k,t})}, \tag{21}$$

where $Raw\Delta^b_{k,t}$ is the fraction of bank trust department traders that buy security k in quarter t. Because $Raw\Delta^b_{k,t}$ is the sum of the number of bank trust departments buying security k this quarter divided by the number of bank trust departments trading the security this quarter, the standardized fraction of bank trust departments buying security k in quarter t can be written as

$$\Delta^b_{k,t} = \frac{\left[\sum_{b=1}^{B_{k,t}} \frac{D_{b,k,t}}{B_{k,t}}\right] - \overline{Raw\Delta^b_t}}{\sigma(Raw\Delta^b_{k,t})}, \tag{22}$$

where $B_{k,t}$ is the number of bank trust departments trading security k in quarter t and $D_{b,k,t}$ is a dummy variable that equals one (zero) if bank trust department b buys (sells) security k in quarter t. The slope coefficient from the regression of the standardized fraction of bank trust departments buying this quarter on the standardized fraction of institutional investors buying last quarter is given as

$$\beta^b_t = \frac{\text{cov}(\Delta^b_{k,t}, \Delta_{k,t-1})}{\sigma^2(\Delta_{k,t-1})} = \frac{\frac{1}{K-1}\sum_{k=1}^{K} \Delta^b_{k,t}\Delta_{k,t-1}}{\sigma^2(\Delta_{k,t-1})} = \frac{1}{K-1}\sum_{k=1}^{K} \Delta^b_{k,t}\Delta_{k,t-1}, \tag{23}$$

where K is the number of securities included in the regression. The numerator in Equation (23) is the cross-sectional covariance between the standardized fraction of bank trust departments buying this quarter and the standardized fraction of institutional investors buying last quarter. Because the data are standardized, the denominator ($\sigma^2(\Delta_{k,t-1})$) in Equation (17) is one, that is, as before, the slope coefficient is the covariance between the standardized data. Moreover, because the cross-sectional standard deviation of the current quarter's fraction of bank trust departments buying is also one (i.e., $\sigma(\Delta^b_{k,t}) = \sigma(\Delta_{k,t-1}) = 1$), the covariance is also equal to the correlation between the two variables.

Substituting Equations (16) and (22) into the right-hand side of Equation (23), an equivalent expression of this correlation (or slope coefficient) is

$$\beta^b_t = \left[\frac{1}{(K-1)\sigma(Raw\Delta^b_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] \sum_{k=1}^{K} \left[\left(\sum_{n=1}^{B_{k,t}} \frac{D_{b,k,t} - \overline{Raw\Delta^b_t}}{B_{k,t}}\right)\left(\sum_{n=1}^{N_{k,t-1}} \frac{D_{n,k,t-1} - \overline{Raw\Delta_{t-1}}}{N_{k,t-1}}\right)\right]. \tag{24}$$

Using the distributive property of the product of sums, Equation (24) can be written as

$$\begin{aligned}
\beta^b_t &= \rho(\Delta^b_{k,t}, \Delta_{k,t-1}) \\
&= \left[\frac{1}{(K-1)\sigma(Raw\Delta^b_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] \sum_{k=1}^{K} \left[\sum_{b=1}^{B_{k,t}} \frac{\left(D_{b,k,t} - \overline{Raw\Delta^b_t}\right)\left(D_{b,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{B_{k,t}N_{k,t-1}}\right] \\
&\quad + \left[\frac{1}{(K-1)\sigma(Raw\Delta^b_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] \\
&\quad \times \sum_{k=1}^{K} \left[\sum_{b=1}^{B_{k,t}} \sum_{m=1,m\neq b}^{N_{k,t-1}} \frac{\left(D_{b,k,t} - \overline{Raw\Delta^b_t}\right)\left(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}}\right)}{B_{k,t}N_{k,t-1}}\right].
\end{aligned} \tag{25}$$

The first term on the right-hand side of Equation (25) is the portion of correlation that results from bank trust departments following themselves into and out of the same securities. The second term on the right hand side of Equation (25) is the portion of the correlation that results from bank trust departments following other institutional investors (both other bank trust departments and other non-bank trust department institutional investors) into and out of the same securities.

The second term in Equation (25) can be further partitioned by investor type. Specifically the term can be divided into two components—bank trust departments following other bank trust departments and bank trust departments following other types of institutional investors. Again using the distributive property of the product of sums, Equation (25) can be written as

$$\beta_t^b = \rho(\Delta_{k,t}^b,\ \Delta_{k,t-1})$$

$$= \left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t}^b)\sigma(Raw\Delta_{k,t-1})}\right]\sum_{k=1}^{K}\left[\sum_{b=1}^{B_{k,t}}\frac{\left(D_{b,k,t}-\overline{Raw\Delta_t^b}\right)\left(D_{b,k,t-1}-\overline{Raw\Delta_{t-1}}\right)}{B_{k,t}N_{k,t-1}}\right]$$

$$+\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t}^b)\sigma(Raw\Delta_{k,t-1})}\right]$$

$$\times\sum_{k=1}^{K}\left[\sum_{b=1}^{B_{k,t}}\sum_{m=1,m\neq b,m\in B}^{B_{k,t-1}}\frac{\left(D_{b,k,t}-\overline{Raw\Delta_t^b}\right)\left(D_{m,k,t-1}-\overline{Raw\Delta_{t-1}}\right)}{B_{k,t}N_{k,t-1}}\right]$$

$$+\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t}^b)\sigma(Raw\Delta_{k,t-1})}\right]$$

$$\times\sum_{k=1}^{K}\left[\sum_{b=1}^{B_{k,t}}\sum_{m=1,m\notin B}^{N_{k,t-1}-B_{k,t-1}}\frac{\left(D_{b,k,t}-\overline{Raw\Delta_t^b}\right)\left(D_{m,k,t-1}-\overline{Raw\Delta_{t-1}}\right)}{B_{k,t}N_{k,t-1}}\right]. \tag{26}$$

The first term on the right-hand side of Equation (26) is as defined in Equation (25). The second term in Equation (26) is the portion of correlation that results from bank trust departments following other bank trust departments into and out of the same securities, for example, if bank trust department b buys (sells) security k in quarter t and investor m is a different bank trust department (i.e., $m \in B$, $m \neq b$) that buys (sells) security k in quarter $t-1$, the second term will be positive. Similarly, the third term in Equation (26) is the portion of correlation that results from bank trust departments following other types of institutional investors into and out of the same securities, for example, if bank trust department b buys (sells) security k in quarter t and institutional investor m is not a bank trust department (i.e., $m \notin B$) that buys (sells) security k in quarter $t-1$, the third term will be positive.

References

Banerjee, A., 1992, "A Simple Model of Herd Behavior," *American Economic Review*, 88, 724–748.

Barberis, N., and A. Shleifer, 2001, "Style Investing," working paper, University of Chicago and Harvard University.

Barboza, D., 1998, "Marketplace Amid Market Turmoil, Small Investor is Steadfast," *New York Times*, August 13, D1.

Bennett, J., R. Sias, and L. Starks, 2003, "Greener Pastures and the Impact of Dynamic Institutional Preferences," *Review of Financial Studies*, 16, 1203–1238.

Bikhchandani, S., D. Hirshleifer, and I. Welch, 1992, "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy*, 100, 992–1026.

Cai, F., G. Kaul, and L. Zheng, 2000, "Institutional Trading and Stock Returns," working paper, University of Michigan.

Campbell, J., M. Lettau, B. Malkiel, and Y. Xu, 2001, "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *Journal of Finance*, 56, 1–43.

Chakravarty, S., 2001, "Stealth Trading: Which Traders' Trades Move Prices?" *Journal of Financial Economics*, 61, 289–307.

Chan, L. K. C., and J. Lakonishok, 1995, "The Behavior of Stock Prices Around Institutional Trades," *Journal of Finance*, 50, 1147–1174.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, "Market Liquidity and Trading Activity," *Journal of Finance*, 56, 501–530.

Cunniff, J., 2000, "Don't Blame the Public," Associated Press wire story, February 15.

Del Guercio, D., 1996, "The Distorting Effect of the Prudent-man Laws on Institutional Equity Investment," *Journal of Financial Economics*, 40, 31–62.

Dennis, P., and J. Weston, 2000, "Who's Informed? An Analysis of Stock Ownership and Informed Trading," working paper, University of Virginia and Rice University.

Dreman, D., 1979, *Contrarian Investment Strategy: The Psychology of Stock Market Success*, Random House, New York.

Falkenstein, E. G., 1996, "Preferences for Stock Characteristics as Revealed by Mutual Fund Portfolio Holdings," *Journal of Finance*, 51, 111–135.

Friedman, B. M., 1984, "A Comment: Stock Prices and Social Dynamics," *Brookings Papers on Economic Activity*, 2, 504–508.

Froot, K. A., D. S. Scharfstein, and J. C. Stein, 1992, "Herd on the Street: Informational Inefficiencies in a Market with Short-term Speculation," *Journal of Finance*, 47, 1461–1484.

Gompers, P., and A. Metrick, 2001, "Institutional Investors and Equity Prices," *Quarterly Journal of Economics*, 116, 229–260.

Graham, J. R., 1999, "Herding Among Investment Newsletters: Theory and Evidence," *Journal of Finance*, 54, 237–268.

Grinblatt, M., and S. Titman, 1989, "Portfolio Performance Evaluation: Old Issues and New Insights," *Review of Financial Studies*, 2, 393–422.

Grinblatt, M., and S. Titman, 1993, "Performance Measurement without Benchmarks: An Examination of Mutual Fund Returns," *Journal of Business*, 66, 47–68.

Grinblatt, M., S. Titman, and R. Wermers, 1995, "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior," *American Economic Review*, 85, 1088–1105.

Grossman, S., and M. Miller, 1988, "Liquidity and Market Structure," *Journal of Finance*, 73, 617–633.

Hirshleifer, D., A. Subrahmanyam, and S. Titman, 1994, "Security Analysis and Trading Patterns When Some Investors Receive Information Before Others," *Journal of Finance*, 49, 1665–1698.

Jones, S., D. Lee, and E. Weis, 1999, "Herding and Feedback Trading by Different Types of Institutions and the Effects on Stock Prices," working paper, Indiana University—Indianapolis, Kennesaw State University, and Merrill Lynch.

Keim, D. B., and A. Madhavan, 1995, "Anatomy of the Trading Process: Empirical Evidence on the Behavior of Institutional Traders," *Journal of Financial Economics*, 37, 371–398.

Keim, D. B., and A. Madhavan, 1997, "Transactions Costs and Investment Styles: An Inter-Exchange Analysis of Institutional Equity Trades," *Journal of Financial Economics*, 46, 265–292.

Kyle, A. S., 1985, "Continuous Auctions and Insider Trading," *Econometrica*, 53, 1315–1335.

Lakonishok, J., A. Shleifer, and R. W. Vishny, 1992, "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics*, 32, 23–43.

Lucchetti, A., and J. Angwin, 2002, "Janus Hastens to Unload Shares in AOL," *Wall Street Journal*, February 20, C1.

Nofsinger, J., and R. W. Sias, 1999, "Herding and Feedback Trading by Institutional and Individual Investors," *Journal of Finance*, 54, 2263–2295.

Parrino, R., R. Sias, and L. Starks, 2002, "Voting with Their Feet: Ownership Changes Around the Time of Forced CEO Turnover," *Journal of Financial Economics*, 68, 3–46.

Pirinsky, C., 2002, "Herding and Contrarian Trading of Institutional Investors," working paper, Texas A&M University.

Scharfstein, D. S., and J. C. Stein, 1990, "Herd Behavior and Investment," *American Economic Review*, 80, 465–479.

Sias, R., L. Starks, and S. Titman, 2002, "The Price Impact of Institutional Trading," working paper, Washington State University and University of Texas.

Strozinsky, R., 1998, "Inside the Stock Market," available at www.standford.edu/~stroz/.

Trueman, B., 1994, "Analyst Forecasts and Herding Behavior," *Review of Financial Studies*, 7, 97–124.

Wermers, R., 1999, "Mutual Fund Trading and the Impact on Stock Prices," *Journal of Finance*, 54, 581–622.

Wermers, R., 2000, "Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses," *Journal of Finance*, 55, 1655–1695.

Yue, L., 1998, "Large Investors Control Market," *Detroit Free Press*, August 21, available at http://www.freep.com.