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Changes in Institutional Ownership and Stock Returns: Assessment and Methodology*

Although the relation between quarterly changes in institutional investor ownership and contemporaneous stock returns is well documented, the source of the relation remains unclear because institutional ownership data are unavailable at higher frequencies. In this study, we develop a method to generate estimates of higher frequency covariances when one variable is observed at lower frequencies (e.g., quarterly changes in institutional ownership and monthly stock returns). Our method provides evidence that institutional trading has both temporary and permanent price effects and that the latter is associated with information effects.

I. Introduction

A central question in finance is the relation between stock returns and changes in ownership by institutional investors. Because institutional investors are required to reveal their portfolio holdings only at quarterly intervals, researchers typically evaluate the relation between quarterly changes in institutional ownership and same-quarter returns, even though return data are available at higher frequencies (e.g., monthly). Thus, although there is strong documentation of a contemporaneous relation between quarterly changes in institutional ownership and same-quarter stock returns, the source of the relation remains an open question.[1] The strong positive correlation between quarterly changes in institutional ownership and same-quarter returns is consistent with three hypotheses: (1) insti-

* We thank participants at the 2001 CEPR/JFI Symposium at INSEAD, the 2001 FMA European meeting, the 2001 Western Finance Association meeting, a faculty seminar at the University of Illinois, Harrison Hong, Massimo Massa, Russ Wermers, and especially an anonymous referee. We thank Murat Binay for excellent research assistance. Contact the corresponding author, Richard Sias, at sias@wsu.edu.

1. Using the data for this study, e.g., the cross-sectional correlation between quarterly changes in institutional ownership and same-quarter returns averages 31%.

(*Journal of Business*, 2006, vol. 79, no. 6)

0021-9398/2006/7906-0005$10.00

tutions have information that allows them to time their trades (i.e., changes in institutional ownership are positively correlated with subsequent intraquarter returns), (2) institutional investors tend to be short-term momentum traders (i.e., intraquarter institutional positive feedback trading), and (3) the buying and selling choices of institutions in aggregate have a contemporaneous effect on returns.

In this study we develop a method that allows us to differentiate among these three potential explanations by estimating higher frequency correlations between changes in institutional ownership and lag, contemporaneous, and lead returns. We estimate, for example, the correlation between unobservable monthly changes in institutional ownership and observable monthly returns in each of the previous and following 12 months, thus building a "term structure" of the correlations between monthly changes in institutional ownership and lead and lag monthly returns. Although our focus is on the relation between quarterly changes in institutional ownership and higher frequency returns, this method can be applied to any situation where (1) observational frequencies differ and (2) variables are linear in time (e.g., continuous quarterly returns are the sum of continuous monthly returns).

Our empirical results suggest that most of the correlation between changes in institutional ownership and same-quarter returns arises contemporaneously. For example, our point estimate suggests that 115% of the correlation between quarterly changes in the number of institutional holders and same-quarter returns arises from price movements that occur the same month as the change in ownership. Our estimates also suggest that the monthly contemporaneous relation accounts for more than 100% of the quarterly correlation because the price effects associated with institutional trading contain both permanent and temporary liquidity components and the temporary components are subsequently reversed. Similarly, when we employ weekly returns in our analysis, our results still indicate that the direct effects associated with aggregate institutional trading primarily drive the correlation between quarterly changes in institutional ownership and same-quarter returns and that there is a temporary liquidity component associated with institutional trading.

Our method allows us to infer that institutional trading has direct effects on security returns. At least initially, this inference seems intuitive—if institutions as a group are adding to their holdings of a certain stock, one may expect their buying activity to "push up" the price of the stock. It is important to recognize, however, that the demand for shares from one group of investors must be offset by the supply of shares from another group of investors. Hence, if we believe that aggregate institutional buying causes returns to increase, we are implicitly assuming that selling by noninstitutional investors does not have a countervailing effect. We propose three reasons why this may be the case. The first possibility is that institutional investors' trades require price concessions because they push liquidity providers away from their preferred inventory positions ("temporary liquidity effects"). Second, finite elasticities may drive the relation—if institutional investors (in aggregate) purchase a security and noninstitutional investors' supply curve is upward sloping, then aggregate institutional demand will be correlated with contemporaneous returns. The third possibility is that institutions are better informed than individuals and that this information is revealed through their trading.

Given that the positive correlation between quarterly changes in institutional ownership and same-quarter returns is not significantly offset in subsequent quarters, the quarterly contemporaneous correlation cannot be explained by the first possibility, temporary liquidity effects. We generate two tests to differentiate between the remaining two possibilities (the information and finite elasticities explanations). First, we compare the strength of the relation between contemporaneous stock returns and two different measures of institutional demand: the change in the number of institutions holding the stock and the change in the fraction of shares they hold. If price changes arise from inelasticities, then returns should be more strongly related to changes in the fraction of shares held by institutional investors. That is, the inelasticity explanation suggests that returns should be more strongly related to net institutional order flow (i.e., changes in number of shares held by institutions as a fraction of outstanding shares). However, if price changes arise from information, then changes in the number of institutions holding the stock as well as changes in the fraction of shares held by institutions should be correlated with the return.

To further differentiate between the information and finite elasticities explanations, we examine the relation between manager size and contemporaneous and future returns. We begin by presenting evidence that both small and large institutional investors are likely to hold an information advantage over other investors. However, the small institutional investors (small managers) play a relatively minor role in determining changes in the fraction of shares held by institutions, but they play a more important role in determining changes in the number of institutions holding shares.[2] Thus, we hypothesize that if the contemporaneous relation between institutional demand and returns is driven by finite elasticities, then small institutions should contribute little to the correlation between changes in the number of institutions and contemporaneous returns. Alternatively, if information revealed through trading primarily drives the correlation between changes in institutional demand and contemporaneous returns, then the fraction of the correlation attributed to small managers should be similar to the fraction of the change in the number of institutions accounted for by small managers.

Our results reveal that contemporaneous returns are in fact more strongly related to changes in the number of institutional investors than changes in the fraction of shares held by institutions, which suggests that information plays a central role in generating the correlation between holdings and returns. In

2. Our use of the term "small institution" here is a relative term referring to the institutions in our data set with less than the median equity assets under management. All of the institutions in our data set have at least $100 million in assets.

addition, consistent with the information hypothesis, we find that the fraction of the correlation between change in the number of institutions and same-quarter returns attributed to small managers is nearly identical to the fraction of the change in the number of institutions attributed to small managers. Thus, even though small institutions have little impact on institutional order flow imbalance, small managers play a relatively large role in determining the correlation between the change in the number of institutions and contemporaneous returns.

The balance of the article is organized as follows. We discuss related research in the next section. In Section III we discuss the data and examine the relations between quarterly changes in institutional ownership and quarterly returns. We develop the methodology in Section IV and examine the role of intraquarter feedback trading, price impacts, and price forecasting in explaining the quarterly correlation in Section V. We estimate the "term structure" of institutional trading in Section VI. Section VII provides robustness tests and a discussion of the limitations of our methodology. Our conclusions are presented in the final section.

II. Related Research

A number of recent studies document positive correlations between aggregate changes in institutional ownership and returns measured over the same quarter or year (see Jones, Lee, and Weis 1999; Nofsinger and Sias 1999; Wermers 1999, 2000; Cai, Kaul, and Zheng 2000; Bennett, Sias, and Starks 2003; Parrino, Sias, and Starks 2003).[3] As noted above, there are three potential explanations for these patterns: changes in institutional ownership lead intraquarter returns, changes in institutional ownership lag intraquarter returns, or changes in institutional ownership have direct effects on security returns. Understanding the source of the correlation between quarterly changes in aggregate institutional ownership and same-quarter returns is important because each explanation has very different interpretations of how markets influence aggregate institutional trading and how aggregate institutional trading influences markets. For example, Gompers and Metrick (2001) argue that return effects associated with upward sloping supply curves, shifts in institutional demand curves, and institutional investors' historical preference for large capitalization stocks explain the disappearance of the small firm effect in recent years. If, however, there are no return effects associated with aggregate institutional ownership changes, then institutional demand shifts cannot explain such phenomena. Similarly, Sias (2004) documents that institutional investors follow each other into and out of the same securities ("herd").

3. In an early study, Kraus and Stoll (1972) use data from the SEC's Institutional Investor Study to examine the relation between returns and trading by 229 institutions over 1968–69. The results of their analysis suggest that changes in ownership by their sample of institutions are positively correlated with returns the same month.

The cause and effects of institutional herding (see, e.g., Friedman 1984; Scharfstein and Stein 1990; Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992; Froot, Scharfstein, and Stein 1992; Hirshleifer, Subrahmanyam, and Titman 1994; Trueman 1994; Barberis and Shleifer 2003) depend critically upon whether there are return effects associated with such herding.

A. Institutional Positive Feedback Trading

Quarterly changes in institutional ownership will be positively correlated with same-quarter returns if institutional investors (noninstitutional investors) follow short-term intraquarter positive (negative) feedback trading strategies. This explanation is consistent with theoretical models that suggest that smart investors may rationally engage in positive feedback trading strategies (e.g., Cutler, Poterba, and Summers 1990; DeLong et al. 1990; Hong and Stein 1999). Moreover, consistent with the momentum trading explanation, recent empirical studies provide evidence that institutional investors tend to purchase (sell) stocks that performed well (poorly) in the recent past (e.g., Grinblatt, Titman, and Wermers 1995; Nofsinger and Sias 1999; Wermers 1999, 2000; Cai, Kaul, and Zheng 2000; Bennett et al. 2003; Parrino et al. 2003; Sias 2004, forthcoming).[4] Further evidence is provided by Odean (1998), who reports that individual investors are more likely to sell past winners than losers (i.e., negative feedback trade).

B. Institutions' Forecasting Intraquarter Prices

The documented correlation between quarterly changes in institutional ownership and same-quarter returns is also consistent with the hypothesis that aggregate institutional trading has no effect on returns, but institutional investors are able to forecast intraquarter returns. Thus, stocks that institutions purchase would outperform those that they sell, and changes in institutional ownership would lead intraquarter returns. Recent studies provide evidence supporting this hypothesis in that measures of aggregate institutional demand are weakly positively correlated with subsequent returns (see Grinblatt and Titman 1989, 1993; Daniel et al. 1997; Nofsinger and Sias 1999; Wermers 1999, 2000; Chen, Jegadeesh, and Wermers 2000; Bennett et al. 2003; Parrino et al. 2003; Sias 2004, forthcoming). These results suggest that at least some of the contemporaneous quarterly correlation could be explained by institutional investors' ability to forecast intraquarter returns. Chen, Hong, and Stein (2002) provide an alternative but similar explanation. They argue that changes in the number of mutual funds holding a security should forecast future returns because short sale constraints keep pessimistic investors' valuations from being immediately reflected in security prices.

4. Evidence of institutional momentum trading, however, is not universal (see, e.g., Badrinath and Wahal 2002). See Sias (forthcoming) for a detailed discussion of differences across institutional momentum trading studies.

C. Direct Effects of Institutional Ownership Changes

The third potential explanation is that aggregate institutional ownership changes have direct effects on security returns. Several studies find evidence that the individual trades of institutional investors have direct effects on prices. For example, Keim and Madhavan (1997) evaluate the trades for 21 institutions over a 26-month period and find that, on average, institutional investors buy stocks at a 0.31% premium and sell stocks at 0.34% discount relative to their previous day's close. Similarly, Chan and Lakonishok (1995) evaluate the trades of 37 investment managers over an 18-month period and find evidence that individual institutional investors' trades have both temporary and permanent effects. If, as the sample of trades from these studies suggest, the trades of individual institutional investors have price effects, then aggregate institutional trading will have price effects, that is, aggregate institutional trading will reflect the cumulative effect of individual institutional investor's trades.

Return effects may be associated with aggregate institutional trading for three reasons: short-term liquidity effects, imperfect substitution (finite elasticities), and information revealed through institutional trading. Aggregate institutional trading may have temporary liquidity effects if institutional investors' trades require price concessions, on average, because they push liquidity providers away from their preferred inventory positions (Stoll 1978; Grossman and Miller 1988) or because liquidity providers incur a cost for processing orders (Demsetz 1968). As noted in the introduction, such liquidity effects are, by definition, temporary and therefore are unlikely to be primarily responsible for the strong positive correlation between quarterly changes in institutional ownership and same-quarter returns. This is not to say that there are no liquidity effects associated with institutional trading, only that such effects cannot fully account for the correlation between quarterly changes in institutional ownership and same-quarter returns.

A growing literature argues that investors view securities as imperfect substitutes (i.e., long-term supply and demand curves have finite elasticities), and limits to arbitrage allow long-term mispricing (Scholes 1972; Shleifer 1986; Bagwell 1991, 1992; Loderer, Cooney, and Van Drunen 1991; Lynch and Mendenhall 1997). If institutional investors purchase a security, and supply curves are upward sloping, then aggregate institutional demand will have direct effects on returns.

Alternatively, due to economies of scale, institutional investors are likely to be better informed than other traders. If trading by institutional investors reveals information, then institutional trading will affect prices (Easley and O'Hara 1987; Kyle 1995). Consistent with this explanation, recent evidence suggests that institutional investors are better informed than other investors (see Sec. II.B).[5] Last, a number of empirical tests suggest that information

5. Szewczyk, Tsetsekos, and Varma (1992), Alangar, Bathala, and Rao (1999), Bartov, Rad-

revealed through trading is primarily responsible for stock price changes (Scholes 1972; French and Roll 1986; Barclay, Litzenberger, and Warner 1990). If, in fact, information revealed through trading is the primary source of stock price changes and institutional investors are more likely to be informed than individual investors, then aggregate institutional trading will have return effects.

III. Quarterly Changes in Institutional Ownership and Quarterly Returns

We compute daily, weekly, monthly, and quarterly continuous returns for all New York Stock Exchange (NYSE) securities with data from the Center for Research in Security Prices (CRSP). Each firm's institutional holdings (from CDA Spectrum) are derived from 13(f) filings for each quarter from December 1979 through December 2000, a total of 85 quarters.[6] CDA Spectrum classifies each institution as one of five "types" according to Standard and Poor's definition of the institution's primary line of business: bank trust departments, insurance companies, investment companies, independent investment advisers, and others.[7]

To be included in the sample for a given quarter, a firm must be listed on the New York Stock Exchange, have beginning-of-quarter capitalization data, and have institutional ownership data at the beginning and end of the quarter. In addition, to minimize the effects of nonsynchronous trading and to ensure that lead and lag estimates are derived from the same sample, we require each security to have return data for each trading day from the 15 months preceding the quarter to the 15 months following the quarter and nonzero volume for

hakrishnan, and Krinsky (2000), and Dennis and Weston (2000) provide additional evidence that institutional investors are better informed than other investors.

6. The 1975 revision to the Securities Exchange Acts requires institutional investment managers with $100 million or more in exchange-traded or NASDAQ-quoted equity securities under management to file 13(f) reports within 45 days of the end of each calendar quarter. Institutions are required to report all equity positions greater than either 10,000 shares or $200,000 in market value. The reporting institutions constitute the majority of institutional holdings. For example, in 1990, the total market value of the equity holdings of institutions filing 13(f) reports (and thus included in the CDA Spectrum database) accounts for 89% of the Conference Board estimate of total institutional investor equity holdings. The remaining 11% of institutional holdings not reported to the SEC include hedge funds, specialist firms, some public pension funds, and small money managers.

7. The "others" category encompasses foundations, university endowments, Employee Stock Option Plans, internally managed pension funds, and individuals who invest others' money who are not otherwise categorized. The classifications are inexact in that institutions file 13(f) reports in the aggregate and some institutions would qualify as more than one type. For example, investment companies that also act as independent investment advisers are classified as investment companies if more than 50% of their assets are in investment companies and as independent investment advisers otherwise. CDA Spectrum/Thompson Financial began a different classification scheme at the end of 1998. For our study, classifications from December 1998–2000 were based on the manager's classification as of September 1998. If the manager did not appear prior to 1998, classifications were based on how similarly classified firms were classified prior to December 1998.

at least 90% of those days. (As discussed in Sec. IV.D, our estimator determines the 15-month criterion.) Moreover, to ensure that our results are not driven by outliers or potential errors in the reported ownership data, we eliminate the 0.5% of the observations in the tails of the distributions of changes in the number of institutional investors and changes in the fraction of shares held by institutional investors. The resulting sample size ranges from a minimum of 1,181 firms in the second quarter of 1981 to a maximum of 2,152 firms in the second quarter of 1998, for a total of 130,817 firm-quarters of data.

We consider two measures for net institutional demand: the change in the number of institutions that hold the firm's shares and the change in the fraction of shares held by institutions.[8] We compute the quarterly change in the number of institutional investors (henceforth, "Δnumber") for each firm as the difference between the number of institutional shareholders at the beginning and end of the quarter.[9] We similarly compute the quarterly change in the fraction of shares held by institutional investors (henceforth, "Δfraction") as the difference between the fraction of shares held by institutional investors at the beginning and end of the quarter, where institutional fractional ownership for each firm-quarter is computed as the total number of that firm's shares held by institutional investors divided by that firm's shares outstanding. Panel A in table 1 reports the time-series average of the 84 cross-sectional averages and 84 cross-sectional standard deviations for the number of, and changes in the number of, institutional investors. Panels B and C report analogous statistics for the fraction of shares held by institutions and continuously compounded quarterly returns, respectively.[10]

The growing importance of institutional investors is depicted in figures 1 and 2. Specifically, for each quarter from March 1980 through December 2000, we report in figure 1 the cross-sectional average number of institutional investors holding each security overall and by type. Similarly, in figure 2 we report the average fraction of shares held by institutional investors in aggregate and by type. On average, across all 84 quarters, the average firm has 90 institutional investors who together hold approximately 36% of their shares. This average reflects growth in the average number of institutions holding a

8. Previous literature primarily focuses on these two measures of institutional demand. Nofsinger and Sias (1999), e.g., use changes in the fraction of shares held by institutions, while Chen et al. (2002) focus on changes in the number of institutions holding a firm's shares. Specifically, Chen, Hong, and Stein hypothesize that because many institutions are reluctant to take short positions, bearish investors are "sidelined" and therefore news is incorporated into prices slowly. As a result, changes in investor breadth (measured as the number of mutual funds holding shares in a security) will forecast security returns.

9. Because 13(f) reporting is aggregated across different units within an institution, the number of institutions reflects the number of unrelated institutions holding the stock.

10. Our analysis is based on continuously compounded raw returns. Because the correlation estimates are cross-sectional, adjusting returns for the continuously compounded market return yields identical results. In addition, the time-series average of mean cross-sectional discrete quarterly return is 3.66%. The difference between the mean continuously compounded and discrete returns arises from the fact that, except for the case of zero return, continuously compounded returns are uniformly smaller than discrete returns.

TABLE 1 **Descriptive Statistics: Time-Series Average of Cross-sectional Values**

	A. Number of Institutions Holding Shares			
	Number of Institutional Investors		Change in Number of Institutions	
	Mean	SD	Mean	SD
Total	89.72	105.70	1.54	7.94
Bank trust departments	32.41	38.88	.22	3.30
Insurance companies	7.96	8.74	.11	1.37
Mutual funds	6.75	7.22	.16	1.46
Independent advisers	34.21	42.87	.76	4.52
Unclassified	8.39	10.70	.29	1.68
	B. Fraction of Shares Held by Institutions			
	% of Shares Held by Institutions		Change in % of Shares Held	
	Mean	SD	Mean	SD
Total	35.73	22.18	.35	4.00
Bank trust departments	8.65	7.53	−.01	1.87
Insurance companies	3.47	4.83	.02	1.29
Mutual funds	5.15	5.21	.10	1.70
Independent advisers	15.47	11.16	.19	3.02
Unclassified	2.98	4.51	.05	1.20
	C. Quarterly Returns (in Percent)			
	Mean	SD		
Quarterly returns	1.94	15.87		

Note.—Each quarter between 1979:4 and 2000:4 (for a total of 84 quarters), we estimate the cross-sectional mean and standard deviation of the number of institutional investors holding each security, changes in the number of institutions holding each security, the fraction of each firm's shares held by institutional investors, changes in the fraction of shares held by institutions, and continuously compounded quarterly returns. We report the time-series average of cross-sectional means and standard deviations above. The sample size ranges from 1,181 firms in 1981:2 to 2,152 firms in 1998:2.

firm's shares from 54 in 1980 to 125 in 2000. It also reflects growth in the average fraction of a firm's shares held by institutions from 24% in 1980 to 44% in 2000. The figures indicate changes over time in the relative dominance of different types of institutions. Consistent with Gompers and Metrick (2001), independent investment advisers drive most of the growth in institutional ownership over the sample period.

For each quarter, we compute the cross-sectional correlations between the two institutional demand variables and quarterly returns measured over three periods: the previous quarter, the same quarter, and the following quarter. The time-series averages of the quarterly cross-sectional correlations are reported in the first row of table 2, where Δnumber is used for the correlations reported in panel A and Δfraction is used for the correlations reported in panel B. The other rows in table 2 report the time-series mean quarterly correlations for each investor type. The *t*-statistics (reported in parentheses) are computed from the time series of the 84 cross-sectional correlations and are based on Newey and West (1987) standard errors with four lags.

Across all institutional categories, there is a strong correlation between

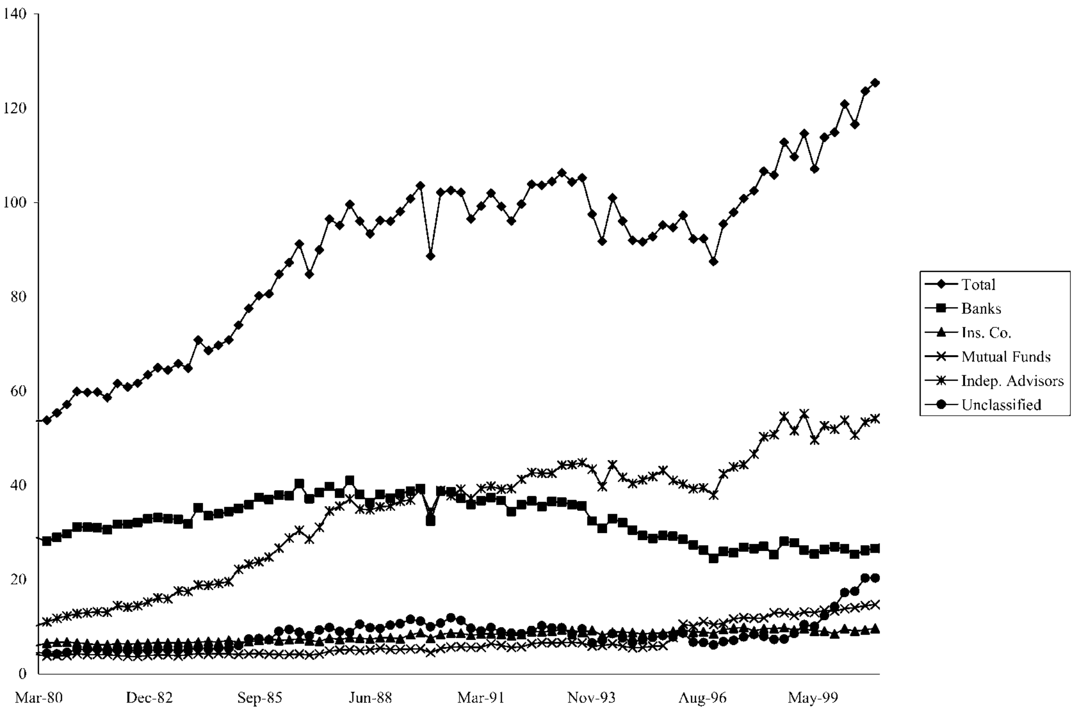

FIG. 1.—Average number of institutions holding shares. This figure shows the cross-sectional average number of institutions holding shares in NYSE companies each quarter from March 1980 to December 2000.

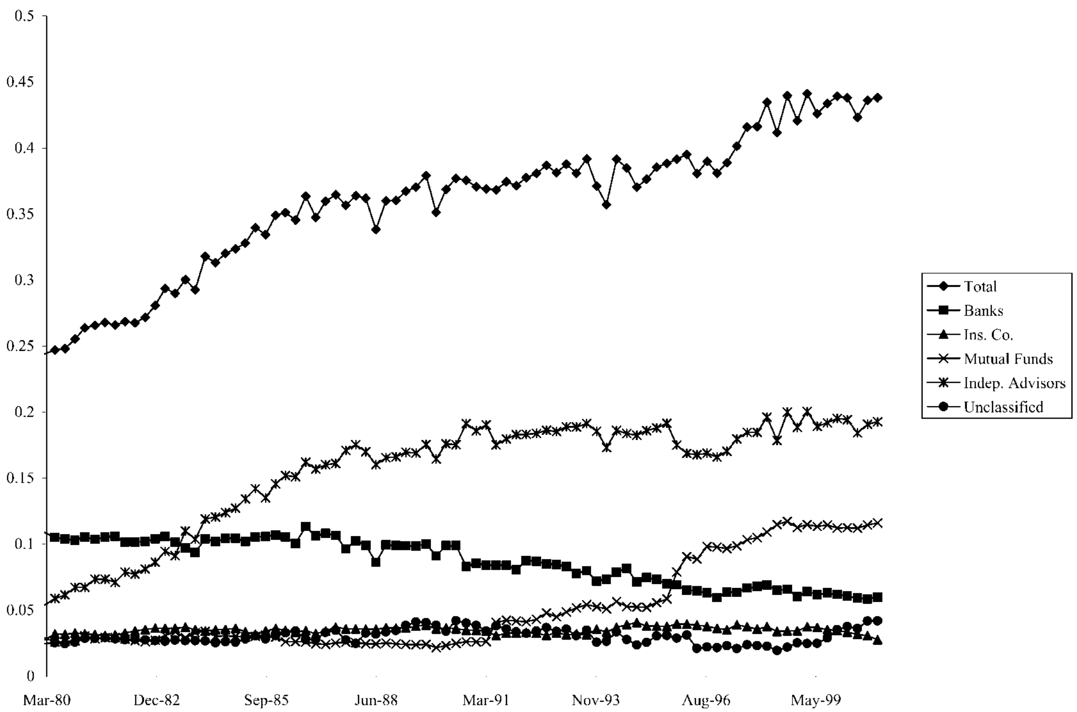

FIG. 2.—Fraction of shares held by institutions. This figure shows the fraction of shares of NYSE companies held by institutions reporting holdings each quarter from March 1980 to December 2000.

TABLE 2 **Average Correlations between Quarterly Changes in Institutional Ownership and Return over the Prior, Same, and Following Quarters Overall and by Investor Type**

	A. Change in Number of Institutions			B. Change in Fraction of Shares Held by Institutions		
Investor	Prior Quarter	Same Quarter	Following Quarter	Prior Quarter	Same Quarter	Following Quarter
All institutions	.1572 (16.73)**	.3110 (32.28)**	.0205 (2.72)**	.0962 (10.66)**	.1596 (15.40)**	.0076 (1.20)
Bank trusts	.0875 (10.41)**	.2046 (18.29)**	.0028 (.40)	.0454 (8.05)**	.0376 (5.71)**	−.0010 (−.19)
Insurance companies	.0777 (11.50)**	.1101 (12.19)**	.0001 (.02)	.0191 (4.20)**	.0313 (6.89)**	−.0063 (−1.82)
Mutual funds	.0929 (11.70)**	.1794 (13.09)**	.0250 (5.21)**	.0519 (7.86)**	.1104 (7.80)**	.0124 (2.48)*
Independent advisers	.1238 (13.52)**	.2570 (30.09)**	.0222 (3.70)**	.0609 (7.29)**	.1191 (14.63)**	.0077 (1.80)
Others	.0644 (9.26)**	.0718 (6.66)**	.0063 (1.34)	−.0019 (−.35)	−.0274 (−3.30)**	−.0022 (−.91)

NOTE.—Each quarter between 1979:4 and 2000:4 (for a total of 84 quarters), we estimate the cross-sectional correlation between changes in institutional ownership (overall and by investor type) for each security and returns measured over the previous, same, and following quarters for all NYSE stocks with adequate data. The sample size ranges from 1,181 firms in 1981:2 to 2,152 firms in 1998:2. The table reports time-series mean correlation coefficients and associated *t*-statistics (computed from the time-series of the 84 cross-sectional correlations and based on Newey and West [1987] standard errors with four lags). Panel A presents results for institutional demand measured by changes in the number of institutions holding shares, while panel B presents results for the measure based on changes in the fraction of shares held by institutions.

* Indicates statistical significance at the 5% level.

** Indicates statistical significance at the 1% level.

Δnumber and returns measured over the contemporaneous quarter as well as the previous quarter. Only mutual funds and independent advisers, however, exhibit statistically significant relations between changes in ownership and returns the following quarter. This result is consistent with the notion that the managers at some of these institutions have superior information.[11] Except for institutions classified as "others," similar results are found when institutional demand is measured by Δfraction (table 2, panel B).

We can quantify the strength of the relation between institutional demand and same-quarter returns by multiplying the standard deviation of returns with the appropriate correlation. As shown in table 1, over the 84 quarters we evaluate, the cross-sectional standard deviations of quarterly returns, Δnumber, and Δfraction average 15.87%, 7.94 institutional investors, and 4.00%, respectively. Thus, a two standard deviation increase in Δnumber means, on average, a 9.9% (2 × 0.3110 × 0.1587) larger return. Similarly, a two standard deviation increase in the Δfraction means a 5.1% (2 × 0.1596 × 0.1587) larger return on average.

In summary, table 2 provides evidence that is consistent with the hypothesis that the strong correlation between quarterly returns and contemporaneous changes in institutional ownership is primarily due to either return effects associated with aggregate institutional trading or institutional momentum trading. The correlation between changes in institutional holdings and returns during the prior quarter indicates that institutions tend to buy winners and sell losers, suggesting that, at least over some intervals, institutions engage in positive feedback trading. The weaker positive correlation between ownership changes and future returns is consistent with the hypothesis that some institutions have superior information or exploit return momentum.

IV. Partitioning Quarterly Correlations into Monthly Relations

In this section, we develop estimates of higher frequency covariances between changes in institutional ownership and lag, contemporaneous, and lead returns. The key to the decomposition is that, although institutional ownership data are only available on a quarterly basis, we can use higher frequency return data (e.g., monthly) and exploit covariance linearity.

A. The Covariance between Quarterly Institutional Ownership Changes and Monthly Returns

Define the continuous return over month t as r_t and the continuous return from the beginning of month A through the end of month B as $r_{A,B}$. Similarly,

11. As Daniel et al. (1997) note, positive correlation between changes in institutional ownership and subsequent returns might arise from stock return momentum if institutional investors tilt their portfolios toward stocks with recent strong performance. Consistent with this hypothesis, the results in table 2 reveal that mutual funds and independent advisers exhibit the strongest correlation with prior quarter returns. It is also possible that changes in institutional ownership are positively correlated with future returns because the stocks institutional investors buy are, in some sense, temporarily riskier.

define the change in institutional ownership (measured as either Δnumber or Δfraction) in month t as Δ_t and the change from the beginning of month A to the end of month B as $\Delta_{A,B}$. For the quarter ending in month $t = 2$ then, the continuous return can be written as the sum of the three monthly returns:

$$r_{0,2} = r_0 + r_1 + r_2, \tag{1}$$

and the quarterly change in institutional ownership given by $\Delta_{0,2}$ can be written as the sum of the changes for each month:

$$\Delta_{0,2} = \Delta_0 + \Delta_1 + \Delta_2. \tag{2}$$

Thus, the covariance between quarterly changes in ownership and returns over the same quarter can be represented by

$$\mathrm{Cov}(\Delta_{0,2}, r_{0,2}) = \mathrm{Cov}(\Delta_0 + \Delta_1 + \Delta_2, r_0 + r_1 + r_2). \tag{3}$$

Because covariances are linear in the arguments, we can decompose this covariance into its parts:

$$\begin{aligned} \mathrm{Cov}(\Delta_{0,2}, r_{0,2}) = {} & \mathrm{Cov}(\Delta_0, r_0) + \mathrm{Cov}(\Delta_1, r_0) + \mathrm{Cov}(\Delta_2, r_0) \\ & + \mathrm{Cov}(\Delta_0, r_1) + \mathrm{Cov}(\Delta_1, r_1) + \mathrm{Cov}(\Delta_2, r_1) \\ & + \mathrm{Cov}(\Delta_0, r_2) + \mathrm{Cov}(\Delta_1, r_2) + \mathrm{Cov}(\Delta_2, r_2). \end{aligned} \tag{4}$$

The first, fifth, and last terms (i.e., $\mathrm{Cov}(\Delta_0, r_0)$,$\mathrm{Cov}(\Delta_1, r_1)$, and $\mathrm{Cov}(\Delta_2, r_2)$) on the right-hand side of equation (4) are the monthly contemporaneous covariances, that is, the covariance between changes in institutional ownership in a given month and returns in that month. The second and sixth terms (i.e., $\mathrm{Cov}(\Delta_1, r_0)$ and $\mathrm{Cov}(\Delta_2, r_1)$) are the lag 1-month feedback trading terms, that is, the covariance between changes in institutional ownership in a given month and returns over the previous month. Similarly, the third term, $\mathrm{Cov}(\Delta_2, r_0)$, measures institutional feedback trading at a 2-month lag. Analogously, the fourth, seventh, and eighth terms (i.e., $\mathrm{Cov}(\Delta_0, r_1)$, $\mathrm{Cov}(\Delta_0, r_2)$, and $\mathrm{Cov}(\Delta_1, r_2)$), represent the covariance between monthly changes in institutional ownership and returns measured over the first or second subsequent month within the quarter.

Ideally, we would measure each term in equation (4) to estimate the relations between monthly changes in institutional ownership and returns measured over the previous, same, and following months. Unfortunately, because institutional investors are only mandated to report holdings quarterly, direct estimation is not possible. Our methodology, however, exploits the fact that we can directly estimate each “row” of equation (4). Panel A in table 3 reports these decompositions: contemporaneous (*C*), lag by *t* months (*Lt*), and lead (forward) by *t* months (*Ft*). As shown in the fifth row of covariances, for example, the covariance between quarterly changes in institutional ownership and returns over the first month in the quarter (Cov($\Delta_{0,2}$, r_0)) consists of a contemporaneous monthly covariance (*C*), a lag 1-month covariance (*L1*), and a lag 2-month covariance (*L2*).

We employ the additive properties of the observable covariances in the first column of table 3 to obtain an estimate of the unobservable covariances in the last column of the table. In particular, as shown in panel B of table 3, the expected value of the difference between the covariance of quarterly ownership changes and the return over the first month of the quarter ("Covariance 0" in panel A) and the covariance between quarterly ownership changes and the return over the month preceding the quarter ("Covariance -1" in panel A) is the contemporaneous covariance less the lag 3-month covariance,

$$\begin{aligned} E[\mathrm{Cov}(\Delta_{0,2}, r_0) - \mathrm{Cov}(\Delta_{0,2}, r_{-1})] &= \mathrm{Cov}(C) + \mathrm{Cov}(L1) + \mathrm{Cov}(L2) \\ &\quad - \mathrm{Cov}(L1) - \mathrm{Cov}(L2) - \mathrm{Cov}(L3) \\ &= \mathrm{Cov}(C) - \mathrm{Cov}(L3). \end{aligned} \tag{5}$$

Assuming $E(\mathrm{Cov}(L3)) = 0$ (i.e., on average, monthly changes in institutional ownership are independent of returns 3 months prior), then equation (5) provides an unbiased estimate of the covariance between monthly changes in ownership and returns the same month.

By the same process, we can generate a second estimate of the covariance between monthly changes in institutional ownership and returns in the same month by taking the difference between the covariance for the last month in the quarter and the covariance for the first month following the quarter. Specifically, as shown in panel C of table 3, the "end-of-quarter" estimate is given by

$$E[\mathrm{Cov}(\Delta_{0,2}, r_2) - \mathrm{Cov}(\Delta_{0,2}, r_3)] = \mathrm{Cov}(C) - \mathrm{Cov}(F3). \tag{6}$$

Similarly, by taking the difference between the covariances for quarterly changes in institutional ownership and different lag returns, each quarter we can generate two estimates of each lead and lag covariance. For example, the beginning-of-quarter lag 1-month covariance can be estimated as the difference between the covariance of quarterly changes in institutional ownership and returns in the month prior to the quarter (i.e., $\mathrm{Cov}(\Delta_{0,2}, r_{-1})$) and the covariance between quarterly changes in institutional ownership and returns 2 months prior to the quarter (i.e., $\mathrm{Cov}(\Delta_{0,2}, r_{-2})$). Analogously, we can generate a second estimate from end-of-quarter covariances. Specifically, the two lag 1-month covariance estimates are given by

$$E[\mathrm{Cov}(\Delta_{0,2}, r_{-1}) - \mathrm{Cov}(\Delta_{0,2}, r_{-2})] = \mathrm{Cov}(L1) - \mathrm{Cov}(L4), \tag{7}$$

$$E[\mathrm{Cov}(\Delta_{0,2}, r_1) - \mathrm{Cov}(\Delta_{0,2}, r_2)] = \mathrm{Cov}(L1) - \mathrm{Cov}(F2). \tag{8}$$

TABLE 3 Decomposition of Covariance between Quarterly Changes in Institutional Ownership and Quarterly Returns

A. Covariance of Quarterly Institutional Ownership Change with Monthly Returns

Covariance −4	$\mathrm{Cov}(\Delta_{0,2}, r_{-4})$	$\mathrm{Cov}(\Delta_0, r_{-4})$	Lag 4 months	*L4*
		$\mathrm{Cov}(\Delta_1, r_{-4})$	Lag 5 months	*L5*
		$\mathrm{Cov}(\Delta_2, r_{-4})$	Lag 6 months	*L6*
Covariance −3	$\mathrm{Cov}(\Delta_{0,2}, r_{-3})$	$\mathrm{Cov}(\Delta_0, r_{-3})$	Lag 3 months	*L3*
		$\mathrm{Cov}(\Delta_1, r_{-3})$	Lag 4 months	*L4*
		$\mathrm{Cov}(\Delta_2, r_{-3})$	Lag 5 months	*L5*
Covariance −2	$\mathrm{Cov}(\Delta_{0,2}, r_{-2})$	$\mathrm{Cov}(\Delta_0, r_{-2})$	Lag 2 months	*L2*
		$\mathrm{Cov}(\Delta_1, r_{-2})$	Lag 3 months	*L3*
		$\mathrm{Cov}(\Delta_2, r_{-2})$	Lag 4 months	*L4*
Covariance −1	$\mathrm{Cov}(\Delta_{0,2}, r_{-1})$	$\mathrm{Cov}(\Delta_0, r_{-1})$	Lag 1 month	*L1*
		$\mathrm{Cov}(\Delta_1, r_{-1})$	Lag 2 months	*L2*
		$\mathrm{Cov}(\Delta_2, r_{-1})$	Lag 3 months	*L3*
Covariance 0	$\mathrm{Cov}(\Delta_{0,2}, r_0)$	$\mathrm{Cov}(\Delta_0, r_0)$	Contemporaneous	*C*
		$\mathrm{Cov}(\Delta_1, r_0)$	Lag 1 month	*L1*
		$\mathrm{Cov}(\Delta_2, r_0)$	Lag 2 months	*L2*
Covariance 1	$\mathrm{Cov}(\Delta_{0,2}, r_1)$	$\mathrm{Cov}(\Delta_0, r_1)$	Lead 1 month	*F1*
		$\mathrm{Cov}(\Delta_1, r_1)$	Contemporaneous	*C*
		$\mathrm{Cov}(\Delta_2, r_1)$	Lag 1 month	*L1*
Covariance 2	$\mathrm{Cov}(\Delta_{0,2}, r_2)$	$\mathrm{Cov}(\Delta_0, r_2)$	Lead 2 months	*F2*
		$\mathrm{Cov}(\Delta_1, r_2)$	Lead 1 month	*F1*
		$\mathrm{Cov}(\Delta_2, r_2)$	Contemporaneous	*C*
Covariance 3	$\mathrm{Cov}(\Delta_{0,2}, r_3)$	$\mathrm{Cov}(\Delta_0, r_3)$	Lead 3 months	*F3*
		$\mathrm{Cov}(\Delta_1, r_3)$	Lead 2 months	*F2*
		$\mathrm{Cov}(\Delta_2, r_3)$	Lead 1 months	*F1*
Covariance 4	$\mathrm{Cov}(\Delta_{0,2}, r_4)$	$\mathrm{Cov}(\Delta_0, r_4)$	Lead 4 months	*F4*
		$\mathrm{Cov}(\Delta_1, r_4)$	Lead 3 months	*F3*
		$\mathrm{Cov}(\Delta_2, r_4)$	Lead 2 months	*F2*
Covariance 5	$\mathrm{Cov}(\Delta_{0,2}, r_5)$	$\mathrm{Cov}(\Delta_0, r_5)$	Lead 5 months	*F5*
		$\mathrm{Cov}(\Delta_1, r_5)$	Lead 4 months	*F4*
		$\mathrm{Cov}(\Delta_2, r_5)$	Lead 3 months	*F3*
Covariance 6	$\mathrm{Cov}(\Delta_{0,2}, r_6)$	$\mathrm{Cov}(\Delta_0, r_6)$	Lead 6 months	*F6*
		$\mathrm{Cov}(\Delta_1, r_6)$	Lead 5 months	*F5*
		$\mathrm{Cov}(\Delta_2, r_6)$	Lead 4 months	*F4*

B. One-Difference Beginning-of-Quarter Estimation of Monthly Contemporaneous Covariance

$$\mathrm{Cov}(\Delta_{0,2}, r_0) - \mathrm{Cov}(\Delta_{0,2}, r_{-1}) = \text{Covariance 0 less Covariance} - 1$$
$$= [C + L1 + L2] - [L1 + L2 + L3]$$
$$= C - L3$$

C. One-Difference End-of-Quarter Estimation of Monthly Contemporaneous Covariance

$$\mathrm{Cov}(\Delta_{0,2}, r_2) - \mathrm{Cov}(\Delta_{0,2}, r_3) = \text{Covariance 2 less Covariance 3}$$
$$= [C + F1 + F2] - [F1 + F2 + F3]$$
$$= C - F3$$

TABLE 3 **(*Continued*)**

D. Two-Difference Beginning-of-Quarter Estimation of Monthly Contemporaneous Covariance
$\mathrm{Cov}(\Delta_{0,2}, r_0) - \mathrm{Cov}(\Delta_{0,2}, r_{-1}) + \mathrm{Cov}(\Delta_{0,2}, r_{-3}) - \mathrm{Cov}(\Delta_{0,2}, r_{-4})$ = Covariance 0 less Covariance − 1 plus Covariance − 3 less Covariance − 4 $= [C + L1 + L2] - [L1 + L2 + L3] + [L3 + L4 + L5] - [L4 + L5 + L6]$ $= C - L6$
E. Two-Difference End-of-Quarter Estimation of Monthly Contemporaneous Covariance
$\mathrm{Cov}(\Delta_{0,2}, r_2) - \mathrm{Cov}(\Delta_{0,2}, r_3) + \mathrm{Cov}(\Delta_{0,2}, r_5) - \mathrm{Cov}(\Delta_{0,2}, r_6)$ = Covariance 2 less Covariance 3 plus Covariance 5 less Covariance 6 $= [C + F1 + F2] - [F1 + F2 + F3] + [F3 + F4 + F5] - [F4 + F5 + F6]$ $= C - F6$

NOTE.—This table shows the decomposition of the covariance between quarterly changes in institutional ownership and quarterly returns. Panel A shows the covariances of quarterly changes in institutional ownership with each of the monthly returns from 4 months preceding the quarter to 4 months following the quarter. Panel B shows how the observable beginning-of-quarter covariances can be combined to achieve an estimate of the contemporaneous monthly covariance. Panel C shows how the observable end-of-quarter covariances can be combined to achieve a second estimate of the contemporaneous monthly covariance. Panel D shows how a second difference in observable covariances can be added to the beginning-of-quarter estimate given in panel B to move the decomposition error term further from the quarter. Similarly, panel E shows how a second difference in observable covariances can be added to the end-of-quarter estimate given in panel C to move the decomposition error term further from the quarter.

Similarly, the two estimates of the covariance between monthly changes in institutional ownership and returns the following month are given by

$$E[\mathrm{Cov}(\Delta_{0,2}, r_1) - \mathrm{Cov}(\Delta_{0,2}, r_0)] = \mathrm{Cov}(F1) - \mathrm{Cov}(L2), \tag{9}$$

$$E[\mathrm{Cov}(\Delta_{0,2}, r_3) - \mathrm{Cov}(\Delta_{0,2}, r_4)] = \mathrm{Cov}(F1) - \mathrm{Cov}(F4). \tag{10}$$

Because we generate two covariance estimates (a beginning-of-quarter estimate and an end-of-quarter estimate) from each quarter's change in institutional ownership, the estimates are unlikely to be independent. Therefore, we average each quarter's beginning- and end-of-quarter estimates to generate that quarter's single covariance estimate.

B. Correlation Decomposition

Because institutional ownership increases over time (figs. 1 and 2), the covariance of changes in institutional ownership and returns also increases over time. Thus, although the covariance estimates given in equations (5)–(10) are appropriate for a given quarter, the lack of covariance stationarity makes aggregation of the estimates over time problematic. To overcome this issue, we "normalize" the covariance estimates each quarter by dividing by that quarter's cross-sectional standard deviations of quarterly returns and changes in institutional ownership.[12] Note that because our goal is to estimate the portion of the quarterly correlation attributed to monthly comovement, we normalize the monthly covariance estimate by the standard deviation of quarterly ownership changes and returns. Hence, we refer to these estimates as normalized covariances rather than estimated correlations.[13] The normalized estimates of the relation between monthly changes in institutional ownership and returns the same month (analogous to eqq. [5] and [6]), for example, are given by:

$$\textit{Normalized}_{beg} \textit{ estimate of contemporaneous monthly covariance} = \left[\frac{\mathrm{Cov}\,(C)}{\sigma(\Delta_{0,2})\sigma(r_{0,2})} - \frac{\mathrm{Cov}\,(L3)}{\sigma(\Delta_{0,2})\sigma(r_{0,2})}\right], \quad (11)$$

$$\textit{Normalized}_{end} \textit{ estimate of contemporaneous monthly covariance} = \left[\frac{\mathrm{Cov}\,(C)}{\sigma(\Delta_{0,2})\sigma(r_{0,2})} - \frac{\mathrm{Cov}\,(F3)}{\sigma(\Delta_{0,2})\sigma(r_{0,2})}\right]. \quad (12)$$

C. Decomposing Monthly Covariances by Investor Type and Investor Size

Our data partition institutional investors into five groups: bank trust departments, insurance companies, mutual funds, independent investment advisers, and others. Therefore, the total change in the institutional ownership for a stock over any period is simply the sum of the changes in each of the five categories. As before, denote the total change in institutional ownership from the beginning of month A to the end of month B as $\Delta_{A,B}$. Similarly denote the change in ownership by bank trust departments, insurance companies, mutual funds, independent investment advisers, and others over the same period as $\Delta B_{A,B}$, $\Delta I_{A,B}$, $\Delta M_{A,B}$, $\Delta D_{\mathrm{A,B}}$, and $\Delta O_{A,B}$, respectively. Then the co-

12. In unreported tests, we divide the sample into two periods and examine whether covariances and correlations differ across the periods. Although we reject the hypothesis (at the 1% level) that the mean covariance in the early period equals the mean covariance in the later period for both measures of changes in ownership, we cannot reject the hypothesis that the mean correlations are the same in both periods for Δnumber (p-value equals 0.85). Specifically, the correlation averages 0.3092 in the early period and 0.3128 in the more recent period. We do find, however, statistically significant differences in the correlation based on Δfraction (which suggests that the estimates based on Δnumber may be, in some sense, “better”).

13. In Sec. VI, we generate estimates of monthly correlation by dividing the monthly covariance estimates by the standard deviation of monthly returns and the estimated standard deviations of monthly changes in institutional ownership.

variance between the total change in institutional ownership ($\Delta_{A,B}$) and returns over the same period is given by

$$\begin{aligned}\operatorname{Cov}(\Delta_{A,B}, r_{A,B}) = {} & \operatorname{Cov}(\Delta B_{A,B}, r_{A,B}) + \operatorname{Cov}(\Delta I_{A,B}, r_{A,B}) + \operatorname{Cov}(\Delta M_{A,B}, r_{A,B}) \\ & + \operatorname{Cov}(\Delta D_{A,B}, r_{A,B}) + \operatorname{Cov}(\Delta O_{A,B}, r_{A,B}).\end{aligned} \tag{13}$$

Dividing the right- and left-hand sides of equation (13) by the cross-sectional standard deviations of quarterly changes in institutional ownership and quarterly returns allows us to partition the correlation between quarterly changes in institutional ownership and returns the same quarter to each investor group:

$$\begin{aligned}\rho(\Delta_{0,2} r_{0.2}) = {} & \frac{\operatorname{Cov}(\Delta B_{0,2}, r_{0,2})}{\sigma(\Delta_{0,2})\sigma(r_{0,2})} + \frac{\operatorname{Cov}(\Delta I_{0,2}, r_{0,2})}{\sigma(\Delta_{0,2})\sigma(r_{0,2})} + \frac{\operatorname{Cov}(\Delta M_{0,2}, r_{0,2})}{\sigma(\Delta_{0,2})\sigma(r_{0,2})} \\ & + \frac{\operatorname{Cov}(\Delta D_{0,2}, r_{0,2})}{\sigma(\Delta_{0,2})\sigma(r_{0,2})} + \frac{\operatorname{Cov}(\Delta O_{0,2}, r_{0,2})}{\sigma(\Delta_{0,2})\sigma(r_{0,2})}.\end{aligned} \tag{14}$$

Moreover, because the quarterly change in total institutional ownership is simply the sum of the quarterly changes by investor type, each term in any covariance equation can be partitioned by investor type. The estimates of the contemporaneous monthly covariance between changes in ownership by bank trust departments and returns analogous to equations (5) and (6), for example, are given by

$$E[\operatorname{Cov}(\Delta B_{0,2}, r_0) - \operatorname{Cov}(\Delta B_{0,2}, r_{-1})] = \operatorname{Cov}(C_{banks}) - \operatorname{Cov}(L3_{banks}), \tag{15}$$

$$E[\operatorname{Cov}(\Delta B_{0,2}, r_2) - \operatorname{Cov}(\Delta B_{0,2}, r_3)] = \operatorname{Cov}(C_{banks}) - \operatorname{Cov}(F3_{banks}). \tag{16}$$

The same method can be used to partition the correlation (and estimates of shorter-term covariances) between institutional demand and returns the same quarter by investor size. Specifically, rather than partitioning managers by type, we divide managers into large (total portfolio value greater than the median manager's portfolio value) and small (total portfolio value less than median manager's portfolio value) managers each quarter and use the methods described in the previous paragraphs to determine the roles of large and small managers.

D. Generating an Unbiased Estimate

Equations (5) and (6) provide unbiased estimates of the covariance between monthly changes in institutional ownership and returns the same month if changes in institutional ownership are independent of returns 3 months prior (i.e., $\operatorname{Cov}(L3) = 0$) and 3 months following (i.e., $\operatorname{Cov}(F3) = 0$). This will not be the case, however, if institutional investors engage in momentum or contrarian trading based on returns 3 months previous (i.e., $\operatorname{Cov}(L3) > 0$ and

$\text{Cov}(L3) < 0$, respectively). Similarly, changes in institutional ownership will not be independent of returns 3 months forward if institutions forecast prices 3 months forward (i.e., $\text{Cov}(F3) > 0$) or if institutional trading temporarily affects prices and this impact is reversed (at least in part) in the third month following the trading (i.e., $\text{Cov}(F3) < 0$). Henceforth, we refer to these terms as, "decomposition error terms" (e.g., Cov(*L3*) in eq. [5] or Cov(*F3*) in eq. [6]).

If changes in institutional ownership are not independent of returns 3 months previous or 3 months forward, we can still generate unbiased estimates of the monthly contemporaneous covariance as long as changes in institutional ownership are independent of returns at some point in the past and at some point in the future. Specifically, we can add a second difference to the estimate to move the decomposition error term further from the quarter. Consider, for example, adding the covariance between the return for month $t = -3$ ("Covariance -3" in table 3) and the quarterly change in institutional ownership and subtracting the covariance between the return for month $t = -4$ ("Covariance -4" in table 3) and the quarterly change in institutional ownership to equation (5). As shown in panel D of table 3, the expected value of the "first difference" given in equation (5) plus this "second difference" yields

$$E[\text{Cov}(\Delta_{0,2}, r_0) - \text{Cov}(\Delta_{0,2}, r_{-1}) + \text{Cov}(\Delta_{0,2}, r_{-3}) - \text{Cov}(\Delta_{0,2}, r_{-4})] = \text{Cov}(C) - \text{Cov}(L6). \quad (17)$$

Similarly, we can add a "second difference" to the end-of-quarter estimate (eq. [6]) to move the decomposition error term further from the quarter. Specifically, as shown in panel E of table 3, the "two-difference" end-of-quarter estimate of the monthly contemporaneous covariance is given by

$$E[\text{Cov}(\Delta_{0,2}, r_2) - \text{Cov}(\Delta_{0,2}, r_3) + \text{Cov}(\Delta_{0,2}, r_5) - \text{Cov}(\Delta_{0,2}, r_6)] = \text{Cov}(C) - \text{Cov}(F6). \quad (18)$$

Thus, if changes in institutional ownership are independent of the monthly return 6 months prior (i.e., $E(\text{Cov}(L6)) = 0$) and 6 months following (i.e., $E(\text{Cov}(F6)) = 0$), then equations (17) and (18) provide unbiased estimates of the covariance between monthly changes in institutional ownership and returns the same month. Again, however, if changes in institutional ownership are not independent of returns 6 months prior or post, we can further improve the estimate by adding as many differences as needed to reach the point where changes in institutional ownership are independent of lead and lag returns. Two costs, however, are associated with each additional difference. First, additional differences have the potential to add noise to our estimates. For example, if the covariance between quarterly changes in institutional ownership and lag returns reflects both momentum trading and a noise component, then additional differences may add noise to our estimates. Second, additional terms require a longer time series of data to be included in the sample (e.g., eqq. [5] and [6] require returns from 1 month prior [$t = -1$] to 1 month following [$t = 4$] the quarterly change in institutional ownership, while eqq. [17] and [18] require returns from 4 months prior [$t = -4$] to 4 months following [$t = 6$] the quarterly change in institutional ownership).

In this study, we focus on lead and lag estimates up to 12 months following and 12 months previous. Thus, to generate unbiased estimates we must determine (1) the point at which changes in institutional ownership become independent of lead and lag returns and (2) the numbers of differences needed to reach that point. To address the first issue, we must determine at what point changes in institutional ownership become independent of returns. Although we cannot directly estimate the normalized decomposition error term (e.g., $\mathrm{Cov}(L3)/(\sigma(\Delta_{0,2})\sigma(r_{0,2})$ in eq. [11]), we can estimate the average sum given by $[\mathrm{Cov}(L3) + \mathrm{Cov}(L4) + \mathrm{Cov}(L5)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$ as the covariance between the quarterly change in institutional ownership and monthly returns 3 months prior to the beginning of the quarter divided by the cross-sectional standard deviations of quarterly changes in institutional ownership and quarterly returns, that is, $\mathrm{Cov}(\Delta_{0,2}, r_{-3})/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$. Similarly, although we cannot directly estimate the decomposition error term from equation (12) (i.e., $\mathrm{Cov}(F3)/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$), we can estimate the average sum given by $[\mathrm{Cov}(F3) + \mathrm{Cov}(F4) + \mathrm{Cov}(F5)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$ as the normalized covariance between the quarterly change in institutional ownership and returns 3 months following the end of the quarter, that is, $\mathrm{Cov}(\Delta_{0,2}, r_5)/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$.

Table 4 reports the time-series averages of the normalized cross-sectional covariances based on quarterly changes in institutional ownership and returns measured over each of the previous 15 months, each of the 3 months within the quarter, and each of the 15 months following the quarter. The second column shows that these estimates include covariances from lag 17 months (Cov(*L17*)) to lead 17 months (Cov(*F17*)). The third and fourth columns in table 4 report the mean estimate and associated *t*-statistic (based on Newey and West [1987] standard errors with four lags), respectively, based on Δnumber. Similarly, the last two columns report the mean estimate and associated *t*-statistic, respectively, based on Δfraction.

The results in table 4 reveal that normalized covariances are large and differ significantly from zero during the same quarter as the change in institutional ownership (i.e., months $t = 0$, 1, and 2) for both measures. Lag normalized covariances tend to be positive and large (relative to lead normalized covariances), but they decay rapidly as one moves further from the quarter. Lead normalized covariances are substantially smaller than lag covariances, which suggests that end-of-quarter estimates are likely to be less biased than beginning-of-quarter estimates. Beyond a 14-month lag (i.e., $t = -14$) or a 14-month lead (i.e., $t = 16$), the normalized covariances do not, in general, differ significantly from zero. Thus, the results in table 4 suggest that estimates with lead or lag return decomposition error terms beyond 14 months (i.e., greater than Cov(*F14*) or Cov(*L14*)) should yield unbiased estimates.

The number of differences needed to reach at least a 15-month lead or a 15-

TABLE 4 **Average Normalized Covariance between Quarterly Changes in Institutional Ownership and Contemporaneous, Lead, and Lag Monthly Returns**

Time	Defined	Representing Normalized Covariance of Lead/Lag	Δ in Number of Institutions		Δ in % Shares Held	
			Estimate	*t*-Statistic	Estimate	*t*-Statistic
$t = -15$	$[\text{Cov}(\Delta_{0,2}, r_{-15})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L15) + \text{Cov}(L16) + \text{Cov}(L17)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0010	.26	−.0057	−1.64
$t = -14$	$[\text{Cov}(\Delta_{0,2}, r_{-14})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L14) + \text{Cov}(L15) + \text{Cov}(L16)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0004	.08	−.0063	−2.61*
$t = -13$	$[\text{Cov}(\Delta_{0,2}, r_{-13})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L13) + \text{Cov}(L14) + \text{Cov}(L15)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0130	3.60**	−.0012	−.45
$t = -12$	$[\text{Cov}(\Delta_{0,2}, r_{-12})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L12) + \text{Cov}(L13) + \text{Cov}(L14)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0225	6.38**	.0019	.70
$t = -11$	$[\text{Cov}(\Delta_{0,2}, r_{-11})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L11) + \text{Cov}(L12) + \text{Cov}(L13)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0157	3.46**	−.0017	−.49
$t = -10$	$[\text{Cov}(\Delta_{0,2}, r_{-10})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L10) + \text{Cov}(L11) + \text{Cov}(L12)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0243	4.62**	.0031	.91
$t = -9$	$[\text{Cov}(\Delta_{0,2}, r_{-9})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L9) + \text{Cov}(L10) + \text{Cov}(L11)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0203	4.82**	.0039	1.05
$t = -8$	$[\text{Cov}(\Delta_{0,2}, r_{-8})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L8) + \text{Cov}(L9) + \text{Cov}(L10)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0164	4.14**	.0062	2.37*
$t = -7$	$[\text{Cov}(\Delta_{0,2}, r_{-7})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L7) + \text{Cov}(L8) + \text{Cov}(L9)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0212	6.37**	.0011	.38
$t = -6$	$[\text{Cov}(\Delta_{0,2}, r_{-6})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L6) + \text{Cov}(L7) + \text{Cov}(L8)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0355	8.49**	.0101	3.23**
$t = -5$	$[\text{Cov}(\Delta_{0,2}, r_{-5})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L5) + \text{Cov}(L6) + \text{Cov}(L7)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0230	5.16**	.0073	2.34**
$t = -4$	$[\text{Cov}(\Delta_{0,2}, r_{-4})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L4) + \text{Cov}(L5) + \text{Cov}(L6)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0306	8.29**	.0144	5.35**
$t = -3$	$[\text{Cov}(\Delta_{0,2}, r_{-3})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L3) + \text{Cov}(L4) + \text{Cov}(L5)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0434	8.02**	.0237	6.10**
$t = -2$	$[\text{Cov}(\Delta_{0,2}, r_{-2})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L2) + \text{Cov}(L3) + \text{Cov}(L4)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0451	12.57**	.0272	8.53**
$t = -1$	$[\text{Cov}(\Delta_{0,2}, r_{-1})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(L1) + \text{Cov}(L2) + \text{Cov}(L3)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0699	14.54**	.0464	12.45**
$t = 0$	$[\text{Cov}(\Delta_{0,2}, r_{0})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(C) + \text{Cov}(L1) + \text{Cov}(L2)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.1324	26.40**	.0729	15.85**

$t = 1$	$[\text{Cov}(\Delta_{0,2}, r_1)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F1) + \text{Cov}(C) + \text{Cov}(L1)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0945	17.74**	.0473	10.26**
$t = 2$	$[\text{Cov}(\Delta_{0,2}, r_2)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F2) + \text{Cov}(F1) + \text{Cov}(C)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0842	17.57**	.0394	9.62**
$t = 3$	$[\text{Cov}(\Delta_{0,2}, r_3)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F3) + \text{Cov}(F2) + \text{Cov}(F1)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0055	.96	−.0029	−.77
$t = 4$	$[\text{Cov}(\Delta_{0,2}, r_4)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F4) + \text{Cov}(F3) + \text{Cov}(F2)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0015	.30	.0037	1.30
$t = 5$	$[\text{Cov}(\Delta_{0,2}, r_5)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F5) + \text{Cov}(F4) + \text{Cov}(F3)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0180	3.63**	.0086	3.04**
$t = 6$	$[\text{Cov}(\Delta_{0,2}, r_6)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F6) + \text{Cov}(F5) + \text{Cov}(F4)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0030	.44	−.0005	−.08
$t = 7$	$[\text{Cov}(\Delta_{0,2}, r_7)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F7) + \text{Cov}(F6) + \text{Cov}(F5)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0074	1.70	.0090	2.96**
$t = 8$	$[\text{Cov}(\Delta_{0,2}, r_8)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F8) + \text{Cov}(F7) + \text{Cov}(F6)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0198	6.01**	.0094	3.22**
$t = 9$	$[\text{Cov}(\Delta_{0,2}, r_9)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F9) + \text{Cov}(F8) + \text{Cov}(F7)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	−.0040	−.70	−.0018	−.62
$t = 10$	$[\text{Cov}(\Delta_{0,2}, r_{10})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F10) + \text{Cov}(F9) + \text{Cov}(F8)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0079	1.38	.0019	.63
$t = 11$	$[\text{Cov}(\Delta_{0,2}, r_{11})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F11) + \text{Cov}(F10) + \text{Cov}(F9)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0134	2.31*	.0076	2.81**
$t = 12$	$[\text{Cov}(\Delta_{0,2}, r_{12})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F12) + \text{Cov}(F11) + \text{Cov}(F10)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0027	.51	−.0032	−1.00
$t = 13$	$[\text{Cov}(\Delta_{0,2}, r_{13})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F13) + \text{Cov}(F12) + \text{Cov}(F11)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0046	.96	.0038	1.11
$t = 14$	$[\text{Cov}(\Delta_{0,2}, r_{14})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F14) + \text{Cov}(F13) + \text{Cov}(F12)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	.0072	1.58	.0084	3.27**
$t = 15$	$[\text{Cov}(\Delta_{0,2}, r_{15})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F15) + \text{Cov}(F14) + \text{Cov}(F13)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	−.0089	−1.80	−.0031	−1.23
$t = 16$	$[\text{Cov}(\Delta_{0,2}, r_{16})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F16) + \text{Cov}(F15) + \text{Cov}(F14)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	−.0041	−.90	−.0040	−2.00*
$t = 17$	$[\text{Cov}(\Delta_{0,2}, r_{17})]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	$[\text{Cov}(F17) + \text{Cov}(F16) + \text{Cov}(F15)]/[\sigma(\Delta_{0,2})\sigma(r_{0,2})]$	−.0001	−.03	.0013	.54

NOTE.—Each quarter between 1979:4 and 2000:4 (for a total of 84 quarters), we estimate the cross-sectional covariance between quarterly changes in institutional ownership and returns measured over each of the previous 15 months, each of the 3 months within the quarter ($t = 0$ to $t = 2$), and each of the 15 months following the quarter. The covariances are then "normalized" by dividing each quarter's estimate by the cross-sectional standard deviations of that quarter's returns and changes in the institutional ownership. The time-series mean normalized covariance (and associated t-statistic) is reported for the measured based on changes in the number of institutions (cols. 3 and 4) and the measure based on changes in the fraction of shares held by institutions (cols. 5 and 6). The t-statistics are based on Newey and West (1987) standard errors (with four lags) computed from time-series variation in the 84 normalized covariance estimates.

* Indicates statistical significance at the 5% level.

** Indicates statistical significance at the 1% level.

month lag is a function of the particular lead or lag being estimated. Because we use monthly data in partitioning the quarterly results, each additional difference for every month increases the decomposition error term by 3 months. As a result, we can generate estimates that have 15-month decomposition error terms only for one in 3 months. Thus, we use the number of differences needed to generate decomposition error terms of 15, 16, or 17 months. Specifically, the number of differences needed to generate a 15-, 16-, or 17-month decomposition error term for the beginning-of-quarter estimate of lag month X (where X is negative for lead values) is solved by determining

$$15 \leq [X + (3 \times \text{number of differences})] \leq 17. \tag{19}$$

Similarly, the number of differences needed for the end-of-quarter estimate of lag month X is solved by determining

$$-15 \leq [X - (3 \times \text{number of differences})] \leq -17. \tag{20}$$

Thus, for example, the lag 8-month estimate (i.e., Cov($L8$)) requires three differences for the beginning-of-quarter estimate (eq. [19]) and eight differences for the end-of-quarter estimate (eq. [20]). One to nine differences are need to solve equations (19) and (20) for the lag 12-month to lead 12-month estimates that are the focus of our study. These estimates require returns up to 15 months prior to the quarter and 15 months following the quarter. As discussed in the Section III, we therefore require firms to have complete return data available for the 15 months prior to, and the 15 months following, the quarterly change in institutional ownership to be included in the sample.

V. The Importance of Feedback Trading, Price Impacts, and Return Forecasting

As discussed in the introduction, the correlation between quarterly returns and contemporaneous quarterly changes in institutional ownership could arise from the institutions' intraquarter momentum trading, direct effects of their trading, or their ability to time their trades. In this section, we employ the method developed in Section IV to estimate the relative importance of these explanations.

A. Monthly Estimates

As noted above (see eq. [4]), the contemporaneous quarterly correlation consists of three normalized contemporaneous monthly covariances, two normalized lag 1-month covariances, one normalized lag 2-month covariance, two normalized lead 1-month covariances, and one normalized lead 2-month covariance. Because the quarterly correlation contains three normalized monthly contemporaneous covariances, we estimate the contribution of the normalized monthly contemporaneous covariance to the quarterly covariance as three times the estimated normalized monthly contemporaneous covariance.

(Multiplying these estimates by a constant does not affect the *t*-statistics.) Moreover, because the correlation between the quarterly change in institutional ownership and same-quarter returns is simply the covariance divided by the standard deviations of each, three times the normalized covariance estimate is an estimate of the portion of the quarterly correlation attributed to price movements that occur the same month as the change in institutional ownership. Similarly, because there are two lag 1-month covariances and two lead 1-month covariances, the 1-month lead and 1-month lag contributions are given as two times the normalized estimates.

The 85 quarters of data yield a total of 84 quarterly correlations and estimates of normalized lead, contemporaneous, and lag monthly covariances. The first row in table 5 reports the time-series average of the 84 cross-sectional correlations between Δnumber and returns the same quarter. The other columns in the first row partition this correlation by investor type (next five columns; see eq. [14]) and by investor size (last two columns). The estimated portion of the quarterly correlation due to correlation between monthly changes in institutional ownership and returns the same month is reported in the middle row of panel A (second column). The first column reports the fraction of the quarterly correlation accounted for by the comovement between monthly changes in institutional ownership and returns the same month, that is, the number in the "Total" column divided by the number in the first row of that column. Similarly, the remaining rows report estimates from 2 months prior to 2 months forward (last row). The *t*-statistics (reported in parentheses) are computed from the time series of the 84 quarterly estimates and are based on Newey and West (1987) standard errors with four lags. Panel B repeats the analysis based on Δfraction.

The estimates reported in panel A of table 5 suggest that the relation between monthly Δnumber and returns the same month accounts for 115% of the quarterly correlation (statistically significant at the 1% level). The results also provide evidence that price effects associated with institutional trading have a temporary liquidity component—the relation between monthly Δnumber and returns the following month accounts for, on average, −25% of the quarterly correlation (statistically significant at the 1% level).

The other columns in the middle row of table 5 (panel A) report monthly contemporaneous comovement apportioned to each investor type and by manager size. Similar to the results for institutional investors in aggregate, the contemporaneous relation is by far the dominant source of the quarterly correlation for each type of institutional investor. The partitioned monthly contemporaneous estimate differs significantly (at the 1% level or better) from zero for each of the five investor types and for each of the two investor size categories. The estimated fraction of the quarterly correlation attributed to each investor group accounted for by that investor group's contemporaneous monthly comovement (i.e., the numbers in the middle row of panel A divided by the numbers in the top row in panel A) ranges from 101% for mutual funds to 123% for unclassified institutions. The results in panel B, based on

TABLE 5 Monthly Partitioning of Correlation between Quarterly Changes in Institutional Ownership and Continuous Returns

	Estimate From:								
	% of Quarterly	Total	Banks	Insurance Companies	Mutual Funds	Independent Advisers	Others	Large Managers	Small Managers
	A. Estimates Based on Change in Number of Institutional Investors								
Quarterly correlation		.3110	.0933	.0196	.0341	.1479	.0161	.2390	.0720
		(32.28)**	(9.09)**	(14.49)**	(13.03)**	(20.40)**	(4.63)**	(29.06)**	(23.12)**
Institutions following return 2 months previous	−.55	−.0017	−.0044	−.0015	.0008	.0037	−.0002	.0020	−.0037
		(−.16)	(−1.26)	(−1.19)	(.57)	(.62)	(−.10)	(.26)	(−1.00)
Institutions following previous month's return	8.94	.0278	.0132	.0015	.0065	.0062	.0003	.0225	.0054
		(1.11)	(1.38)	(.74)	(2.38)*	(.55)	(.10)	(1.22)	(.63)
Institutions and same month return	115.47	.3591	.1128	.0246	.0344	.1676	.0198	.2706	.0884
		(8.80)**	(6.90)**	(5.42)**	(6.00)**	(7.02)**	(3.50)**	(8.35)**	(8.01)**
Institutions leading next month's return	−25.47	−.0792	−.0287	−.0077	−.0065	−.0298	.0009	−.0565	−.0227
		(−4.30)**	(−3.78)**	(−2.59)*	(−2.29)*	(−2.95)**	(−2.05)*	(−3.88)**	(−3.39)**
Institutions leading return 2 months forward	1.16	.0036	.0328	.0003	.0007	−.0016	.0145	.0017	.0019
		(.34)	(.88)	(.20)	(.58)	(−.30)	(.57)	(.23)	(.54)

	B. Estimates Based on Change in Fraction of Shares Held by Institutions								
Quarterly correlation		.1596	.0186	.0102	.0497	.0900	−.0078	.1553	.0043
		(15.40)**	(5.02)**	(6.89)**	(5.79)**	(14.75)**	(−3.24)**	(13.94)**	(1.91)
Institutions following return 2 months previous	−.38	−.0006	−.0018	.0005	.0025	.0014	−.0032	.0010	−.0016
		(−.09)	(−.74)	(.31)	(.75)	(.29)	(−1.80)	(.15)	(−.73)
Institutions following previous month's return	11.15	.0178	.0038	.0017	.0074	.0028	.0022	.0152	.0026
		(1.55)	(.83)	(.61)	(1.64)	(.30)	(.71)	(1.28)	(.71)
Institutions and same month return	125.63	.2005	.0301	.0081	.0488	.1160	−.0025	.1937	.0068
		(7.77)**	(3.50)**	(1.40)	(3.98)**	(7.79)**	(−.46)	(8.09)**	(1.13)
Institutions leading next month's return	−32.96	−.0526	−.0119	−.0047	−.0078	−.0250	−.0032	−.0490	−.0036
		(−4.52)**	(−2.26)*	(−1.35)	(−1.13)	(−3.17)**	(−.95)	(−4.66)**	(−.91)
Institutions leading return 2 months forward	.69	.0011	.0007	.0022	−.0015	−.0032	.0029	−.0013	.0024
		(.27)	(.35)	(1.29)	(−.58)	(−.75)	(1.73)	(−.36)	(1.44)

NOTE.—Each quarter we estimate the cross-sectional correlation between quarterly changes in the number of institutional investors (panel A) or changes in the fraction of shares held by institutions (panel B) and returns measured over the same quarter. We then decompose the correlation to reveal the portion of the correlation attributed to each investor class (next five columns) and by large and small institutions (last two columns). The first row in each panel reports the time-series average (and associated *t*-statistic) of these 84 cross-sectional quarterly correlations and decomposed correlations. Using the method developed in the article, we then generate an estimate, each quarter, of the contribution of the comovement between monthly changes in institutional ownership and returns the same month to the quarterly correlation. The middle row in each panel reports the time-series average across these 84 estimates. We similarly estimate the contributions of intraquarter feedback trading (first two rows in each panel) and intraquarter price forecasting (last two rows in each panel). The *t*-statistics are based on Newey and West (1987) standard errors (with four lags) computed from time-series variation in the 84 estimates.

* Indicates statistical significance at the 5% level.

** Indicates statistical significance at the 1% level.

Δfraction, are largely consistent with those reported in panel A (based on Δnumber). Specifically, the relation between monthly Δfraction and contemporaneous monthly returns primarily drives the correlation between quarterly Δfraction and returns the same quarter.

In sum, the results presented in table 5 suggest that the correlation between quarterly changes in institutional ownership and returns the same quarter primarily arises from the comovement between monthly changes in institutional ownership and returns the same month. Moreover, the negative normalized covariance for lead monthly returns suggests that the price impact associated with institutional trading has a temporary liquidity component. To examine intramonth effects of aggregate institutional trading, we next extend our analysis to weekly partitioning.

B. Weekly Estimates

Finer partitioning allows us to better isolate the relative importance of return effects associated with aggregate institutional trading versus very short-term (i.e., intramonth) momentum trading or price forecasting. The cost, however, is that the analysis is limited to two estimates each quarter regardless of the interval because the partitioning methodology generates two normalized covariance estimates each quarter (a beginning-of-quarter estimate and an end-of-quarter estimate). In the case of weekly data, for example, we generate two estimates of the weekly contemporaneous normalized covariance each quarter. Because there are 12 weekly contemporaneous covariances each quarter, we estimate the total contribution of the weekly contemporaneous covariances to the quarterly correlation as 12 times the average weekly contemporaneous covariance estimate divided by the cross-sectional standard deviations of quarterly changes in institutional ownership and same-quarter returns. Greater extrapolation, however, results in a noisier estimate.

The number of trading days in any quarter over our sample period ranges from 61 to 64 days. We define the first “weekly” return of the quarter as the first five trading days of the quarter.[14] We similarly define 11 other weekly returns, for a total of 12 weekly returns each quarter.[15] We then estimate the normalized covariance between weekly changes in institutional ownership and returns using formulas analogous to equations (11) and (12).[16] Similarly, we estimate the portion of the correlation between quarterly changes in institutional ownership and returns the same quarter attributed to the comovement

14. Because we can only observe institutional ownership at the beginning and end of each quarter, we define “weeks” as 5–6 consecutive trading days within the quarter.

15. Depending on the number of days in the quarter, 1–4 of the “middle weeks” get an extra trading day. Specifically, in the case of 61 trading days, weeks 1–6 and 8–12 get 5 trading days, and week 7 gets the extra trading day. In the case of 62 trading days, weeks 7 and 8 get the extra days. In the case of 63 trading days, weeks 6, 7, and 8 get the extra trading days. In the case of 64 trading days, weeks 6–9 get the extra trading days.

16. Although the monthly estimates require one to nine differences to yield lead and lag remainders beyond 14 months, the reported weekly estimates require five to seven differences to yield remainders beyond 14 months.

TABLE 6 Weekly Partitioning of Correlation between Quarterly Changes in Institutional Ownership and Continuous Returns

	A. Estimate Based on Changes in Number of Institutional Investors		B. Estimate Based on Changes in Fraction of Shares Held by Institutions	
	Fraction of Quarterly (%)	Total	Fraction of Quarterly (%)	Total
Quarterly correlation		.3110 (32.28)**		.1596 (15.40)**
Institutions following return 3 weeks previous	9.94	.0309 (.56)	−4.95	−.0079 (−.27)
Institutions following return 2 weeks previous	−10.58	−.0329 (−.79)	−8.27	−.0132 (−.42)
Institutions following previous week's return	−10.55	−.0328 (−.65)	8.90	.0142 (.38)
Institutions and same-week return	141.70	.4407 (6.99)**	153.38	.2448 (6.13)**
Institutions following next week's return	−45.47	−.1414 (−2.24)*	−69.30	−.1106 (−2.52)*
Institutions leading returns 2 weeks forward	25.24	.0785 (.98)	31.70	.0506 (1.36)
Institutions leading returns 3 weeks forward	−19.55	−.0608 (−1.05)	−1.82	−.0029 (−.08)

NOTE.—Each quarter we estimate the cross-sectional correlation between quarterly changes in the number of institutional investors (second column) or changes in the fraction of shares held by institutions (fourth column) and returns measured over the same quarter. The first row in each panel reports the time-series average (and associated *t*-statistic) of these 84 cross-sectional quarterly correlations. Using the method developed in the article, we then generate an estimate, each quarter, of the contribution of the comovement between weekly changes in institutional ownership and returns the same week to the quarterly correlation. The middle row in each panel reports the time-series average across these 84 quarterly estimates. We similarly estimate the contributions of intramonth feedback trading (first three rows in each panel) and intramonth price forecasting (last three rows in each panel). The *t*-statistics are based on Newey and West (1987) standard errors (with four lags) computed from time-series variation in the 84 estimates.

* Indicates statistical significance at the 5% level.

** Indicates statistical significance at the 1% level.

between weekly changes in institutional ownership and returns the same week as 12 times the normalized weekly contemporaneous covariance. We estimate analogous contributions for 3 weeks prior and 3 weeks following. We limit the weekly analysis to 3 weeks in each direction to maintain reasonable table sizes and because these estimates capture the relation between monthly changes in institutional ownership and returns the same month. The reader may refer to the previous section for analysis of lead and lag monthly relations.

Panel A in table 6 reports the weekly estimates based on Δnumber, while panel B reports estimates based on Δfraction. The results in table 6 suggest that the positive correlation between quarterly changes in institutional ownership and returns the same quarter is primarily driven by the relation between weekly changes in institutional ownership and returns the same week. Specifically, the middle row of panel A (panel B) reports that the estimated weekly contemporaneous comovement accounts for 141% (153%) of the correlation between Δnumber (Δfraction) and same-quarter returns (both estimates differ from zero at the 1% level). The results in table 6 also reveal evidence that weekly changes in institutional ownership are inversely related to returns the following week, providing further evidence of a temporary liquidity component.[17]

C. Is the Contemporaneous Relation Driven by Information or Finite Elasticities?

The results in this section suggest that the correlation between quarterly changes in institutional ownership and returns the same quarter is primarily driven by the price impact associated with institutional trading. As noted in the introduction, institutional trades may have a permanent contemporaneous effect on returns if either (1) information is revealed through institutional trading or (2) institutional investors face finite elasticities when buying or selling. We generate two tests to differentiate between these explanations. First, we hypothesize that if the relation is driven by finite elasticities, then returns should be more strongly related to Δfraction than Δnumber. That is, if institutions demand a lot of shares, for whatever reason (information or noise), and the price impact of institutional trading is driven by finite elasticities, then returns should move with net institutional order flow.

Second, we demonstrate that although small managers play a relatively minor role in determining institutional order flow, they play a much larger role in determining Δnumber. Moreover, we find evidence that both small and large institutional investors are likely to be better informed than other investors (e.g., individual investors). Thus, we hypothesize that if the contemporaneous relation between institutional demand and returns is driven by finite elasticities, then the fraction of the correlation attributed to small institutions should be relatively minor because small institutions play a minor role in determining institutional order flow imbalance. Alternatively, if information revealed through trading primarily drives the correlation between institutional demand and contemporaneous returns, then the portion of the correlation attributed to small managers should be similar to the portion of the Δnumber attributed to small institutions.

We have already shown in table 2 that returns are more strongly related to Δnumber than Δfraction, suggesting that information revealed through trading primarily drives the correlation.[18] Specifically, the average correlation between

17. Although specific results are not reported, we also compute a daily decomposition to evaluate intraweek relations. Consistent with the monthly and weekly analysis, the results suggest that the quarterly correlation is primarily driven by direct effects of institutional trading. The daily contemporaneous estimate based on Δnumber, for example, is statistically significant at the 1% level and accounts for 116% of the quarterly correlation. In general, however, daily results based on Δfraction are not statistically significant (at traditional levels).

18. These results are also consistent with empirical evidence that price changes are more strongly related to number of trades than share volume (e.g., Jones, Kaul, and Lipson 1994; Jiang and Kryzanowski 1997).

Δnumber and same-quarter returns is 95% greater than the correlation between Δfraction and same-quarter returns (statistically significant at the 1% level).[19]

As an alternative test of the relative strength of the relations between contemporaneous returns and the two measures of changes in institutional holdings, we estimate cross-sectional regressions of contemporaneous quarterly returns on both variables. To allow direct comparison of the estimated coefficients, we standardize (i.e., rescale to zero mean, unit variance) both the dependent and independent variables.[20] The average coefficients from the 84 cross-sectional regressions and associated *t*-statistics (in parentheses, based on the 84 estimates and Newey-West standard errors with four lags) are

$$r_{qtr} = \underset{(8.99)}{0.0886}(\Delta\text{fraction}) + \underset{(30.80)}{0.2894}(\Delta\text{number})$$

According to the *t*-statistics, both coefficients differ significantly from zero at the 1% level. In addition, the average R^2 is 11.51%. The standardized coefficients reveal that a one standard deviation increase in the fraction of shares held by institutional investors is associated with a 0.0886 standard deviation larger quarterly return, while a one standard deviation increase in the number of institutional investors is associated with a 0.2894 standard deviation larger quarterly return. Although the average coefficients for both independent variables differ significantly from zero, the average coefficient associated with Δnumber is over three times the average coefficient associated with Δfraction. Moreover, a paired *t*-test of the hypothesis that the coefficients are equal is rejected at the 1% level (*t*-statistic = 13.88). In sum, the stronger relation between returns and Δnumber than Δfraction is most consistent with the hypothesis that institutional trading affects returns because such trading reveals information.

We next partition institutional investors into two equal-size groups (each quarter)—large institutions (those with portfolio values greater than the median manager's portfolio value) and small institutions (those with portfolio values less than the median manager's portfolio value). As noted in the introduction, we hypothesize that both small and large managers are likely to be better informed than other investors (also see discussion in Sec. II.B). To test this hypothesis, we compute Δnumber and Δfraction for small and large managers.[21] We then compute the cross-sectional correlation between both measures of institutional demand (Δnumber and Δfraction) for both small and large managers and returns the following quarter. Consistent with the hy-

19. A *t*-statistic is computed from a paired *t*-test that the contemporaneous quarterly correlations based on Δnumber equals the contemporaneous quarterly correlation based on Δfraction.

20. Because standardization is a linear rescaling of the original variables, the R^2 is not affected. In addition, because all (rescaled) variables are mean zero, the intercept is zero.

21. Note that the sum of Δnumber (or Δfraction) for all managers is simply the sum of Δnumber (or Δfraction) for small and large managers.

pothesis that both small and large managers are better informed than other investors, Δnumber for both small and large institutions is positively correlated with subsequent quarter returns (statistically significant in both cases at the 5% level).[22]

We next examine the relative roles of small and large managers in determining Δfraction and Δnumber. Specifically, we measure the role of small and large managers by partitioning Δnumber (or Δfraction) by manager size, for example, the fraction of Δnumber due to large (small) managers for security *i* in quarter *t* is the change in the number of large (small) institutions divided by the total change in the number of institutions for security *i* in quarter *t*. We similarly compute the proportion of Δfraction attributed to small and large managers.[23] We then average these estimates across securities each quarter and then across quarters. Not surprisingly, small managers play a relatively small role in determining Δfraction—averaging only 8% (i.e., large managers account for 92% of Δfraction, on average). Small managers, however, play a more important role in determining Δnumber—accounting for, on average, 22% of Δnumber (i.e., large managers account for 78% of Δnumber, on average).

Given that small managers appear to be better informed than non-13(f) (e.g., individual) investors but play a relatively minor role in determining institutional order flow imbalance (Δfraction), we hypothesize that if the contemporaneous relation between institutional demand and returns is driven by finite elasticities, then the fraction of the correlation attributed to small institutions should be relatively minor for both measures of institutional demand (Δfraction and Δnumber). Alternatively, if information revealed through trading primarily drives the correlation between institutional demand and contemporaneous returns, then the fraction of the correlation between Δnumber and contemporaneous returns attributed to small managers should be similar to the portion of Δnumber attributed to small institutions.

Next, we partition the correlation between quarterly returns and both measures of institutional demand into the portion accounted for by small managers and the portion accounted for by large managers (using the method analogous to eq. [14]). In addition, we estimate the portion of the correlation attributed to changes that occur the same month and lead and lag months within the quarter. Results are reported in the last two columns of table 5.

Not surprisingly, given the minor role small managers play in determining institutional order flow imbalance (Δfraction), we find that small managers account for relatively little (approximately 5%) of the correlation between

22. Statistical significance is based on time-series Newey and West (1987) standard errors (with four lags) of the 84 cross-sectional correlations. The correlation between large institutions' demand and subsequent quarter returns averages 1.91% (t-statistic = 2.63) for Δnumber and 0.49% (t-statistic = 0.78) for Δfraction. For small institutions, the correlation averages 1.27% (t-statistic = 2.06) for Δnumber and 0.64% (t-statistic = 2.06) for Δfraction.

23. Note that because Δfraction and Δnumber can be very small (or zero), and we compute the role of small and large managers as a portion of Δfraction and Δnumber, we exclude observations when Δnumber is zero or the absolute value of Δfraction is less than 1%.

Δfraction and returns the same quarter.[24] Consistent with the information explanation, however, small managers account for 23% of the correlation between Δnumber and returns the same quarter (nearly matching the 22% of Δnumber accounted for by small managers). Moreover, for both small and large managers, the relation between institutional demand and returns the same month (middle row) primarily drives the quarterly correlation.

In short, the results in this section are most consistent with the hypothesis that information revealed through trading drives the contemporaneous relation between institutional demand and stock returns. Specifically, returns are more strongly related to Δnumber than institutional order flow imbalance (Δfraction), and although small managers account for little of the institutional order flow imbalance, they account for a substantial portion of the correlation between Δnumber and same-quarter returns.

VI. Estimating Correlations and the "Term Structure" of Institutional Trading

In the previous sections, we normalize higher frequency covariance estimates by dividing by the cross-sectional standard deviations (at time t) of both quarterly changes in institutional ownership and quarterly returns to estimate the relative importance of momentum trading, contemporaneous effects, and price forecasting in explaining the quarterly correlation. The covariance decomposition method, however, also allows us to estimate higher frequency correlations. To estimate monthly correlations, for example, we divide the monthly covariance estimates by (1) the cross-sectional standard deviation of the appropriate monthly return and (2) the estimated cross-sectional standard deviation of monthly changes in institutional ownership. We generate the cross-sectional standard deviation of monthly returns directly. For example, when estimating the correlation between monthly changes in institutional ownership at month $t = 0$ and returns the previous month, we normalize by the cross-sectional standard deviation of monthly returns for month $t = -1$. Because institutional data are only observed quarterly, we infer the monthly cross-sectional standard deviation of changes in institutional ownership by assuming that monthly changes in institutional ownership are independent over time and, as a result, variance is proportional to time.[25] Thus, we estimate

24. Each quarter, we compute the cross-sectional average fraction of Δfraction accounted for by small (and large) managers. The time-series average of this ratio is 5%. Because the average of a ratio is not equivalent to the average of the numerator divided by the average of the denominator, the 5% figure cannot be inferred from table 5. Nonetheless, the results in table 5 show that the time-series average of the numerator (0.0043) accounts for approximately 3% of the time-series average of the denominator (0.1553).

25. Sias (2004) finds evidence that changes in institutional ownership are not independent over time. Nonetheless, the time-series dependence in the change in institutional ownership is sufficiently small that these estimates are likely to be close to their true values. To the extent that institutional investors herd (follow each other into and out of the same securities), our shorter-term correlation estimates will be negatively biased. Any such bias, however, should affect all estimates equally and therefore not affect the relative importance of each.

the cross-sectional standard deviation of monthly changes in institutional ownership as the square root of the cross-sectional variance of quarterly changes in institutional ownership divided by 3 (i.e., the number of months in the quarter).

Given estimates of monthly covariances and monthly standard deviations, we can estimate the correlation between monthly changes in institutional ownership and monthly returns for any lead or lag period. For example, the beginning-of-quarter time t one-difference estimated correlation between monthly changes in institutional ownership and monthly returns 12 months prior is given by

$$\hat{\rho}(\Delta_0 r_{-12}) = \left[\frac{\mathrm{Cov}\,(L12)}{\hat{\sigma}(\Delta_0)\sigma(r_{-12})} - \frac{\mathrm{Cov}\,(L13)}{\hat{\sigma}(\Delta_0)\sigma(r_{-12})}\right]. \tag{21}$$

Similarly, we can generate estimates of the correlation between monthly changes in institutional ownership and cumulative lag monthly returns by summing the covariance estimates and normalizing by the estimated cross-sectional standard deviation of monthly changes in institutional ownership and the cross-sectional standard deviation of the appropriate cumulative returns.[26]

Using the one- to nine-difference covariance estimates discussed in the previous section, we generate beginning- and end-of-quarter estimates of the correlation between monthly changes in institutional ownership and monthly returns over the previous 12 months, the contemporaneous month, and the following 12 months of each of the 84 quarters. The time-series averages of these 84 estimates (i.e., the average of the beginning- and end-of-quarter estimates each quarter) are presented in table 7 (panel A) for both measures of changes in institutional ownership—Δnumber and Δfraction. Similarly, panel B of table 7 presents estimates of the correlation between monthly changes in institutional ownership and cumulative returns over the previous 1–12 months and cumulative returns over the following 1–12 months.

The results in table 7, panel A, reveal a clear spike at the contemporaneous monthly correlation for both measures of changes in institutional ownership consistent with the results in table 5. For example, the estimated monthly correlation between Δnumber and monthly returns of 35.34% means that a two standard deviation increase in the number of institutional investors in a month (approximately 9.2 institutions) implies a 6.8% higher monthly return ($2 \times 0.3534 \times 0.096$).[27] In addition, consistent with temporary liquidity effects, the estimated correlation is negative in the first month following the

26. For example, the beginning-of-quarter estimate of the correlation between monthly changes in institutional ownership and returns over the previous 12 months is normalized by the estimated cross-sectional standard deviation of monthly changes in institutional ownership and the cross-sectional standard deviation of cumulative returns over months $t = -1$ to $t = -12$.

27. A one standard deviation increase in the number of institutional investors is approximately equal to the standard deviation of quarterly Δnumber (7.94 from table 1) divided by the square root of three. The average cross-sectional standard deviation of monthly returns is 9.6%.

TABLE 7 Estimated Correlation between Monthly Changes in Institutional Ownership, Monthly Returns, and Cumulative Monthly Returns

	Based on Change in Number of Institutions		Based on Change in % Shares Held by Institutions			Based on Change in Number of Institutions		Based on Change in % Shares Held by Institutions	
	Average Correlation	*t*-Statistic	Average Correlation	*t*-Statistic		Average Correlation	*t*-Statistic	Average Correlation	*t*-Statistic
	A. Estimated Monthly Correlations					B. Estimated Monthly Cumulative Correlations			
$t = -12$	.1047	3.14**	.0646	2.62*	$t = -12$ to -1	.1208	10.06**	.0610	7.57**
$t = -11$	.0289	1.19	−.0175	−.74	$t = -11$ to -1	.0960	8.13**	.0457	4.77**
$t = -10$	−.0736	−1.92	−.0368	−1.69	$t = -10$ to -1	.0898	5.90**	.0516	5.02**
$t = -9$	.0971	2.66**	.0700	3.38**	$t = -9$ to -1	.1182	11.41**	.0665	9.75**
$t = -8$	.0253	.86	−.0058	−.25	$t = -8$ to -1	.0935	7.22**	.0473	5.58**
$t = -7$	−.0542	−1.40	−.0461	−1.89	$t = -7$ to -1	.0910	5.57**	.0525	4.86**
$t = -6$	.1326	3.24**	.0899	4.15**	$t = -6$ to -1	.1215	11.50**	.0780	13.35**
$t = -5$	−.0145	−.42	−.0182	−.85	$t = -5$ to -1	.0734	4.53**	.0449	4.84**
$t = -4$	−.0279	−.79	−.0263	−1.42	$t = -4$ to -1	.0873	4.70**	.0580	5.26**
$t = -3$	.1659	3.96**	.1138	4.73**	$t = -3$ to -1	.1200	12.55**	.0835	13.21**
$t = -2$	−.0151	−.49	−.0049	−.23	$t = -2$ to -1	.0246	.92	.0157	1.14
$t = -1$	.0450	1.20	.0266	1.54	$t = -1$	.0450	1.20	.0266	1.54
$t = 0$	.3534	8.94**	.1940	7.73**	$t = 0$	.3534	8.94**	.1974	7.73**
$t = 1$	−.1202	−4.54**	−.0765	−4.42**	$t = 1$	−.1202	−4.54**	−.0765	−4.42**
$t = 2$	.0097	.31	.0034	.27	$t = 1$ to 2	−.0767	−2.95**	−.0514	−3.22**
$t = 3$	.1147	3.27**	.0720	3.80**	$t = 1$ to 3	.0026	.25	−.0028	−.36
$t = 4$	−.1298	−4.84**	−.0591	−2.96**	$t = 1$ to 4	−.0641	−4.64**	−.0326	−2.75**
$t = 5$	.0603	3.08**	.0179	1.47	$t = 1$ to 5	−.0287	−2.13	−.0195	−1.82
$t = 6$	.0710	2.15**	.0441	2.54*	$t = 1$ to 6	.0035	.27	−.0008	−.08
$t = 7$	−.1139	−3.56**	−.0290	−1.36	$t = 1$ to 7	−.0410	−3.09**	−.0125	−1.12
$t = 8$	.0970	3.99**	.0191	1.42	$t = 1$ to 8	−.0039	−.37	−.0057	−.59
$t = 9$	.0006	.02	.0148	.75	$t = 1$ to 9	−.0020	−.15	−.0013	−.13
$t = 10$	−.0791	−2.25*	−.0201	−.78	$t = 1$ to 10	−.0271	−2.29*	−.0081	−.75
$t = 11$	.1172	4.36**	.0354	2.00*	$t = 1$ to 11	.0092	1.10	.0032	.37
$t = 12$	−.0361	−1.20	−.0241	−1.14	$t = 1$ to 12	−.0005	−.04	−.0027	−.26

NOTE.—The first column of panel A presents the estimated correlations between monthly changes in the number of institutions holding shares in each security and returns each of the previous 12 months, the same month, and each of the following 12 months. The third column in panel A reports analogous statistics when institutional demand is measured by changes in the fraction of shares held by institutions. The second and fourth columns present the associated *t*-statistic (based on Newey and West [1987] standard errors [with four lags] computed from time-series variation in the 84 quarterly estimates). Panel B presents the estimated correlations (and associated *t*-statistics) between changes in institutional ownership and cumulative lag returns ranging from 1 to 12 months, returns the same month, and cumulative lead returns ranging from 1 to 12 months.

* Indicates statistical significance at the 5% level.

** Indicates statistical significance at the 1% level.

change in institutional ownership. The results also suggest an interesting pattern in institutional momentum trading. Estimates of lag and lead correlations tend to spike at 3-month intervals. This pattern is consistent with the direct estimates of normalized covariances reported in table 4 (i.e., it is not an artifact of our methodology).[28] Although they are beyond the scope of the current study, we plan to further investigate these patterns in future work.[29]

Panel B in table 7 reports the estimated correlations based on lag and lead cumulative monthly returns. The estimated correlations beyond lag 3 months are relatively stable. Thus, although monthly changes in institutional ownership appear to be related to lag returns beyond 3 months (i.e., panel A), incorporating that information provides little marginal gain in the ability to forecast changes in institutional ownership. In addition, although the results in both panels A and B suggest a temporary liquidity component associated with changes in institutional ownership (i.e., negative correlation with returns the month following the change in institutional ownership), the results in panel B show that this is offset by subsequent positive correlation between changes in institutional ownership and returns beyond the following month (i.e., the estimated correlation between monthly changes in institutional ownership and subsequent longer-term cumulative monthly returns is close to zero).

Table 8 reports analogous estimates based on weekly returns. Again, we document a large spike in the contemporaneous weekly correlation and negative correlation between weekly changes in institutional ownership and the subsequent weekly return. The estimated correlation of 40.99% between weekly Δnumber and returns the same week means that a two standard deviation increase in the number of institutional investors in a week (approximately 4.6 institutions) implies a 4.2% higher weekly return ($2 \times 0.4099 \times 0.051$).[30] We also find positive correlation between weekly changes in institutional ownership and weekly returns 12 weeks prior (and post), consistent with the lag 3-month spike for monthly returns. Although estimated lag cumulative correlations are close to zero, lead weekly cumulative correlations tend to be slightly negative. This is primarily driven by the estimated negative correlation between weekly changes in institutional ownership and returns the following week.

Although detailed results are not reported (to conserve space), we also test

28. Moving from the lag 3 month to lag 4 month, e.g., the normalized covariance based on Δnumber (reported in table 4) falls 29%. Similarly, moving from month lag 6 to lag 7 and from month lag 12 to lag 13, the normalized covariance falls 40% and 42%, respectively. Moving from month lag 9 to lag 10, however, the normalized covariance increases 20%.

29. One potential explanation for these patterns is that institutional investors trade more in the last month of a quarter to "window dress" their portfolios. Window dressing refers to institutional investors selling losers and/or buying winners to present "respectable" portfolios to sponsors. However, as we show in the next section, it is unlikely that window dressing can fully explain this pattern.

30. A one standard deviation increase in the number of institutional investors is approximately equal to the standard deviation of quarterly Δnumber (7.94 from table 1) divided by the square root of 12 (the number of weeks in a quarter). The average cross-sectional standard deviation of weekly returns is 5.1%.

TABLE 8 Estimated Correlation between Weekly Changes in Institutional Ownership, Weekly Returns, and Cumulative Weekly Returns

A. Estimated Weekly Correlations

	Based on Change in Number of Institutions		Based on Change in % Shares Held by Institutions	
	Average Correlation	*t*-Statistic	Average Correlation	*t*-Statistic
$t = -12$	.2042	2.88**	.1797	4.81**
$t = -11$	−.0918	−1.42	−.1187	−3.59**
$t = -10$	−.0050	−.06	.0446	1.26
$t = -9$	.0076	.11	.0145	.43
$t = -8$	.0032	.04	−.0439	−1.19
$t = -7$	.0197	.22	.0544	1.24
$t = -6$	−.0387	−.45	−.0448	−1.17
$t = -5$	−.0247	−.40	−.0321	−1.11
$t = -4$	.0756	.84	.0797	2.08*
$t = -3$	.0414	.57	−.0119	−.31
$t = -2$	−.0417	−.88	−.0192	−.52
$t = -1$	−.0447	−.84	.0072	.18
$t = 0$	.4099	6.63**	.2263	6.07**
$t = 1$	−.1355	−2.13*	−.1073	−2.46**
$t = 2$	.0967	1.08	.0595	1.44
$t = 3$	−.0617	−.90	.0020	.05
$t = 4$	−.0274	−.32	−.0547	−1.47
$t = 5$	.0277	.29	.0152	.36
$t = 6$	−.0311	−.35	−.0145	−.36
$t = 7$	−.0383	−.64	−.0477	−1.49
$t = 8$	.0530	.58	.0665	1.73
$t = 9$	−.0103	−.14	−.0337	−.88
$t = 10$	.0166	.33	−.0181	−.54
$t = 11$	−.1631	−3.58**	−.0157	−.39
$t = 12$	.2260	3.43**	.1424	3.59**

B. Estimated Weekly Cumulative Correlations

	Based on Change in Number of Institutions		Based on Change in % Shares Held by Institutions	
	Average Correlation	*t*-Statistic	Average Correlation	*t*-Statistic
$t = -12$ to -1	.0435	3.97**	.0399	7.38**
$t = -11$ to -1	−.0170	−.88	−.0136	−1.11
$t = -10$ to -1	.0146	.85	.0253	1.96
$t = -9$ to -1	.0121	.52	.0102	1.00
$t = -8$ to -1	.0072	.30	.0039	.28
$t = -7$ to -1	.0087	.32	.0227	1.65
$t = -6$ to -1	−.0044	−.16	.0005	.02
$t = -5$ to -1	.0153	.54	.0186	.96
$t = -4$ to -1	.0255	.92	.0343	1.71
$t = -3$ to -1	−.0233	−.56	−.0101	−.37
$t = -2$ to -1	−.0604	−1.57	−.0059	−.23
$t = -1$	−.0447	−.84	.0072	.18
$t = 0$	.4099	6.63**	.2263	6.07**
$t = 1$	−.1355	−2.13*	−.1073	−2.46**
$t = 1$ to 2	−.0347	−.57	−.0336	−1.29
$t = 1$ to 3	−.0681	−1.67	−.0300	−1.90
$t = 1$ to 4	−.0738	−1.84	−.0538	−3.01**
$t = 1$ to 5	−.0532	−1.31	−.0426	−2.15*
$t = 1$ to 6	−.0603	−1.72	−.0405	−2.98**
$t = 1$ to 7	−.0675	−2.53*	−.0575	−4.43**
$t = 1$ to 8	−.0450	−1.57	−.0281	−1.88
$t = 1$ to 9	−.0485	−2.38*	−.0409	−3.25**
$t = 1$ to 10	−.0430	−2.50*	−.0455	−3.86**
$t = 1$ to 11	−.0902	−4.47**	−.0486	−4.08**
$t = 1$ to 12	−.0208	−2.01*	−.0036	−.67

NOTE.—The first column of panel A presents the estimated correlations between weekly changes in the number of institutions holding shares in each security and returns each of the previous 12 weeks, the same week, and each of the following 12 weeks. The third column in panel A reports analogous statistics when institutional demand is measured by changes in the fraction of shares held by institutions. The second and fourth columns present the associated *t*-statistic (based on Newey and West [1987] standard errors [with four lags] computed from time-series variation in the 84 quarterly estimates). Panel B presents the estimated correlations (and associated *t*-statistics) between changes in institutional ownership and cumulative lag returns ranging from 1 to 12 weeks, returns the same week, and cumulative lead returns ranging from 1 to 12 weeks.

* Indicates statistical significance at the 5% level.

** Indicates statistical significance at the 1% level.

whether estimated lead and lag correlations differ across investor types. Specifically, we test whether each lead and lag estimate differs (1) across the five investor classes or (2) across the three "large" investor classes (bank trust departments, mutual funds, and independent advisers). The results, however, reveal very few statistically significant differences.

VII. Robustness Tests and Limitations

A. Potential Bias due to Window Dressing

Our method implicitly assumes that the covariance between changes in institutional ownership and lead or lag returns is independent of the calendar date. For example, equation (5) assumes that the expected value of the covariance between changes in ownership the last month in quarter t and returns in the first month in the quarter ($\mathrm{Cov}_t(\Delta_2, r_0)$) equals the expected value of the covariance between changes in ownership the second month in a quarter and returns 1 month prior to the quarter ($\mathrm{Cov}_t(\Delta_1, r_{-1})$). In other words, we are assuming that the covariance between portfolio changes in December of a given year and returns in October is equal, on average, to the covariance between portfolio changes in November of that year and returns in September. Similarly, our method implicitly assumes that changes in ownership (Δnumber or Δfraction) have the same means across months. One might expect these assumptions to be violated if institutional investors have a tendency to "window dress" at the end of each quarter.

We address the potential window-dressing bias in several ways. First, the limited evidence supporting the window-dressing hypothesis suggests that it occurs only at the turn of the year (see, e.g., Lakonishok et al. 1991). Therefore, we repeat the analyses in tables 5–8 excluding estimates garnered from both the first and last quarters of the year. Our results remain similar to those that include all quarters. For example, the monthly contemporaneous normalized covariance based on Δnumber accounts for 118% of the quarterly correlation when excluding the first and fourth quarters and 115% of the quarterly correlation when including all quarters.

Second, this potential bias is likely to be less important as we move to a finer partitioning of the data. If institutional investors window dress only in the last week in the quarter, the potential bias remains. To the extent that institutional investors begin to window dress in the second week prior to the end of the quarter, the potential bias is diminished.

In sum, although institutional window dressing has the potential to bias our estimates, our results remain intact when we exclude the turn-of-the-year period, and the potential bias is likely to be less important as our partitioning moves to a finer interval (e.g., less important for weekly estimates than monthly estimates).

B. Trade Discreteness

Because aggregate institutional ownership data are available only on a quarterly basis, we exploit the linear properties of covariances to infer the shorter-term relations between aggregate institutional trading and returns. Thus, we do not know when, exactly, the change in ownership occurs. For a given security, it is possible that the entire change in ownership occurs the first day of the quarter, the last day in the quarter, or somewhere in between. Because our analyses are cross-sectional, however, this should not seriously bias our estimates unless the change in ownership occurs systematically across all securities on the same day. Given that institutional investors account for 70% of trading volume (Schwartz and Shapiro 1992), it is unlikely that the change in ownership occurs on a given day or even a few days.

Nonetheless, to ensure that our results are not sensitive to such potential patterns, we repeat the analysis in table 5 for small, medium, and large stocks (stocks are sorted into three equal-size groups each quarter based on market capitalization) separately. We hypothesize that because institutions account for most of the trading volume of medium and large stocks, changes in institutional ownership are more likely to be spread out over the quarter. Thus, if our results are systematically biased by the discreteness in changes in institutional ownership, then the small stock analysis should differ substantially from the medium and large stock analysis.

The analysis by firm size (not reported to conserve space) reveals little evidence that discreteness of ownership changes affects our results. Specifically, the six contemporaneous estimates (small, medium, and large stocks based on Δnumber and Δfraction) are statistically significant (at the 1% level) and account for a minimum of 105% of the quarterly correlation (Δfraction for medium stocks) to a maximum 140% of the quarterly correlation (Δfraction for small stocks).[31] In sum, the estimates by firm size suggest that the relation between quarterly changes in institutional ownership and same-quarter returns is primarily driven by the price impact of institutional trading.

VIII. Conclusions

When examining the relation between two variables with different periodicity, researchers typically focus on the lowest common frequency interval. Because institutional ownership is reported quarterly, for example, researchers typically evaluate the relation between quarterly changes in institutional ownership and quarterly returns even though higher frequency returns data are available. In this study, we develop a method that exploits covariance linearity to generate

31. We also examine the correlations and monthly decompositions for samples sorted on firm size and analysts following. The results, for each sample, are largely consistent with those reported in table 5. Specifically, the quarterly correlation is primarily driven by the monthly contemporaneous covariance in every case.

higher frequency estimates and use this method to evaluate monthly, weekly, and daily relations between returns and changes in institutional ownership.

The strong positive cross-sectional correlation between quarterly changes in institutional ownership and returns the same quarter has three possible sources: (1) intraquarter institutional momentum trading, (2) changes in institutional ownership lead intraquarter returns, and (3) return effects associated with aggregate institutional trading. Our results suggest that most of the correlation between quarterly changes in institutional ownership and returns arises as a result of return effects associated with aggregate institutional trading. In fact, our point estimates suggest that the price impact of institutional trading accounts for more than 100% of the quarterly correlation because it contains a temporary liquidity component.

There are two interpretations of our finding that institutional trading generates the correlation between quarterly changes in institutional ownership and same-quarter returns. The first is that institutional investors are better informed on average and that their information is incorporated into security prices when they trade. The second is that the return effects arise because markets are segmented and there is elasticity in the supply of shares. Consistent with the first interpretation, quarterly returns are more strongly related to changes in the number of institutional investors than in changes in the total number of shares they hold and, despite the fact that small institutions play a minor role in determining institutional order flow (Δfraction), small institutions account for a relatively large role in determining the correlation between Δnumber and returns.

Finally, the method employed in this study can be used in other situations in which it is difficult to determine whether two variables are related on a contemporaneous, lag, or lead basis, because the observational frequency of one variable does not match the other. Examples of such situations include relating exchange rates to macroeconomic variables, foreign investor flows to stock market returns, or mutual fund flows to fund returns.

References

Alangar, Sadhana, Chenchuramaiah T. Bathala, and Ramesh P. Rao. 1999. The effect of institutional interest on the informational content of dividend-change announcements. *Journal of Financial Research* 22 (Winter): 429–48.

Badrinath, S. G., and Sunil Wahal. 2002. Momentum trading by institutions. *Journal of Finance* 57 (December): 2449–78.

Bagwell, Laurie Simon. 1991. Shareholder heterogeneity: Evidence and implications. *American Economic Review* 81 (May): 218–21.

———. 1992. Dutch auction repurchases: An analysis of shareholder heterogeneity. *Journal of Finance* 47 (March): 71–105.

Banerjee, Abhijit V. 1992. A simple model of herd behavior. *Quarterly Journal of Economics* 107 (August): 724–48.

Barberis, Nicholas, and Andrei Shleifer. 2003. Style investing. *Journal of Financial Economics* 68 (May): 161–99.

Barclay, Michael J., Robert H. Litzenberger, and Jerold B. Warner. 1990. Private information, trading volume, and stock-return variances. *Review of Financial Studies* 3:233–53.

Bartov, Eli, Suresh Radhakrishnan, and Itzhak Krinsky. 2000. Investor sophistication and patterns in stock returns after earnings announcements. *Accounting Review* 75 (January): 43–63.

Bennett, James A., Richard W. Sias, and Laura T. Starks. 2003. Greener pastures and the impact of dynamic institutional preferences. *Review of Financial Studies* 16 (Winter): 1203–38.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy* 100 (October): 992–1026.

Cai, Fang, Gautam Kaul, and Lu Zheng. 2000. Institutional trades and stock returns. Unpublished working paper, University of Michigan.

Chan, Louis K. C., and Josef Lakonishok. 1995. The behavior of stock prices around institutional trades. *Journal of Finance* 50 (September): 1147–74.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers. 2000. The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. *Journal of Financial and Quantitative Analysis* 35 (September): 343–68.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein. 2002. Breadth of ownership and stock returns. *Journal of Financial Economics* 66 (November/December): 171–205.

Cutler, David M., James M. Poterba, and Lawrence H. Summers. 1990. Speculative dynamics and the role of feedback traders. *American Economic Review* 80 (May): 63–68.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers. 1997. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance* 52 (July): 1035–58.

DeLong, Bardford J., Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann. 1990. Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance* 45 (June): 379–96.

Demsetz, Harold. 1968. The costs of transacting. *Quarterly Journal of Economics* 82 (February): 33–53.

Dennis, Patrick, and James Weston. 2000. Who's informed? An analysis of stock ownership and informed trading. Working paper, University of Virginia and Rice University.

Easley, David, and Maureen O'Hara. 1987. Price, trade size, and information in securities markets. *Journal of Financial Economics* 19 (September): 69–90.

French, Kenneth R., and Richard Roll. 1986. Stock-return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics* 17 (September): 5–26.

Friedman, Benjamin M. 1984. A comment: Stock prices and social dynamics. *Brookings Papers on Economic Activity* 2:504–8.

Froot, Kenneth A., David S. Scharfstein, and Jeremy C. Stein. 1992. Herd on the street: Informational inefficiencies in a market with short-term speculation. *Journal of Finance* 47 (September): 1461–84.

Gompers, Paul A., and Andrew Metrick. 2001. Institutional investors and equity prices. *Quarterly Journal of Economics* 116 (February): 229–59.

Grinblatt, Mark, and Sheridan Titman. 1989. Portfolio performance evaluation: Old issues and new insights. *Review of Financial Studies* 2:393–422.

———. 1993. Performance measurement without benchmarks: An examination of mutual fund returns. *Journal of Business* 66 (January): 47–68.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers. 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review* 85 (December): 1088–1105.

Grossman, Sanford J., and Merton H. Miller. 1988. Liquidity and market structure. *Journal of Finance* 43 (December): 617–33.

Hirshleifer, David, Avanidhar Subrahmanyam, and Sheridan Titman. 1994. Security analysis and trading patterns when some investors receive information before others. *Journal of Finance* 49 (December): 1665–98.

Hong, Harrison, and Jeremy C. Stein. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54 (December): 2143–84.

Jiang, Li, and Lawrence Kryzanowski. 1997. Trading activity, quoted liquidity, and stock volatility. *Multinational Finance Journal* 1 (September): 199–227.

Jones, Charles M., Gautman Kaul, and Marc L. Lipson. 1994. Information, trading, and volatility. *Journal of Financial Economics* 36 (August): 127–54.

Jones, Steven L., Darrell Lee, and Edward 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, Donald B., and Ananth Madhavan. 1997. Transactions costs and investment style: An inter-exchange analysis of institutional equity trades. *Journal of Financial Economics* 46 (December): 265–92.

Kraus, Alan, and Hans R. Stoll. 1972. Price impacts of block trading on the New York Stock Exchange. *Journal of Finance* 27 (June): 569–88.

Kyle, Albert S. 1995. Continuous auctions and insider trading. *Econometrica* 53 (November): 1315–35.

Lakonishok, Josef, Andrei Shleifer, Richard Thaler, and Robert Vishny. 1991. Window-dressing by pension fund managers. *American Economic Review Papers and Proceedings* 81 (May): 227–31.

Loderer, Claudio, John W. Cooney, and Leonard D. Van Drunen. 1991. The price elasticity of demand for common stock. *Journal of Finance* 46 (June): 621–51.

Lynch, Anthony W., and Richard R. Mendenhall. 1997. New evidence on stock price effects associated with changes in the S&P 500. *Journal of Business* 70 (July): 351–84.

Nofsinger, John R., and Richard W. Sias. 1999. Herding and feedback trading by institutional and individual investors. *Journal of Finance* 54 (December): 2263–95.

Newey, Whitney K., and Kenneth D. West. 1987. A simple, positive semidefinite heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–8.

Odean, Terrance. 1998. Are investors reluctant to realize their losses? *Journal of Finance* 53 (October): 1775–98.

Parrino, Robert, Richard W. Sias, and Laura T. Starks. 2003. Voting with their feet: Ownership changes around the time of CEO turnover. *Journal of Financial Economics* 68 (April): 3–46.

Scharfstein, David S., and Jeremy C. Stein. 1990. Herd behavior and investment. *American Economic Review* 80 (June): 465–79.

Scholes, Myron S. 1972. The market for securities: Substitution versus price pressure and the effects of information on share prices. *Journal of Business* 45 (April): 179–211.

Schwartz, R., and J. Shapiro. 1992. The challenge of institutionalization of the equity market. In *Recent developments in finance*, ed. A. Saunders. New York: New York University Salomon Center.

Shleifer, Andrei. 1986. Do demand curves for stocks slope down? *Journal of Finance* 41 (July): 579–90.

Sias, Richard W. 2004. Institutional herding. *Review of Financial Studies* 17 (Spring): 165–206.

———. Forthcoming. Reconcilable differences: Momentum trading by institutions. *Financial Review*.

Stoll, Hans R. 1978. The supply of dealer services in securities markets. *Journal of Finance* 33 (September): 1133–51.

Szewczyk, Samuel H., George P. Tsetsekos, and Raj Varma. 1992. Institutional ownership and the liquidity of common stock offerings. *Financial Review* 27 (May): 211–25.

Trueman, Brett. 1994. Analyst forecasts and herding behavior. *Review of Financial Studies* 7 (Spring): 97–124.

Wermers, Russ. 1999. Mutual fund trading and the impact on stock prices. *Journal of Finance* 54 (April): 581–622.

———. 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses. *Journal of Finance* 55 (August): 1655–95.