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Momentum Trading by Institutions

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ABSTRACT

We document the equity trading practices of approximately 1,200 institutions from the third quarter of 1987 through the third quarter of 1995. We decompose trading by institutions into the initiation of new positions (entry), the termination of previous positions (exit), and adjustments to ongoing holdings. Institutions act as momentum traders when they enter stocks but as contrarian traders when they exit or make adjustments to ongoing holdings. We find significant differences in trading practices among different types of institutions.

IN A CELEBRATED ARTICLE published almost a half century ago, Friedman (1953) argues that rational speculation *must* stabilize asset prices. More recently, DeLong et al. (1990) show that momentum traders (also referred to as trend chasers or positive feedback traders) can, in fact, destabilize stock prices and thereby threaten the efficiency of financial markets. DeLong et al.'s proof has inspired numerous empirical investigations that focus almost exclusively on the behavior of institutional investors. There are at least two reasons for this focus. First, a large fraction of corporate equity is held by institutional investors; institutional ownership of shares in U.S. firms increased from approximately 7 percent in 1950 to over 50 percent in 1999 (Federal Reserve Board, 2000). Second, institutions are frequently alleged to herd and to follow potentially destabilizing investment strategies (see, e.g., Lakonishok, Shleifer, and Vishny (1992a)).[1] DeLong et al. note that trend

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[1] The correlation between changes in institutional ownership and other equity market phenomena has also not gone unnoticed. Campbell et al. (2001) document an increase in firm-level volatility between 1962 and 1997 and speculate that the increase in institutional ownership may be responsible for this effect. Malkiel and Xu (1999) find evidence consistent with this idea. Other studies suggest that institutional trading might be responsible for the turn-of-the-year effect (Sias and Starks (1997a)), serial correlation in daily returns (Sias and Starks (1997b)), the small-firm effect (Gompers and Metrick (2001)), or cross-autocorrelation in equity returns (Badrinath, Kale, and Noe (1995)).

chasing can cause momentum (or positive autocorrelation) in stock prices. This causal link between trend chasing and price momentum also underlies Hong and Stein's (1999) behavioral model, in which trading by one class of agents produces momentum in stock prices. Hong and Stein's model explicitly requires the presence of momentum traders, and in a discussion of the empirical implications of their model, they specifically point to momentum trading by institutions.

A growing number of empirical studies address momentum trading by institutions, with somewhat conflicting results. Lakonishok et al. (1992a) analyze the quarterly holdings of a sample of pension funds and find little evidence of momentum trading. Grinblatt, Titman, and Wermers (1995) examine the quarterly holdings of 274 mutual funds and find that 77 percent of the funds in their sample engage in momentum trading (see also Wermers (1999)). Nofsinger and Sias (1999) examine total institutional holdings of individual stocks and find evidence of intraperiod momentum trading. Using a different sample, Gompers and Metrick (2001) investigate the relation between institutional holdings and lagged returns and conclude that once they control for firm size, there is no evidence of momentum trading.

These studies are limited in their ability to capture the full range of institutional trading practices, in part because they restrict their cross-sectional analysis to particular subsets of institutions. Lakonishok et al. (1992a) consider only pension funds, and Grinblatt et al. (1995) and Wermers (1999) consider only mutual funds. They are also limited because they examine aggregate institutional holdings in a firm (as in Nofsinger and Sias (1999) and Gompers and Metrick (2001)). Since different institutions are often buyers and sellers in the same securities, aggregating their holdings obscures the correlation between changes in *individual* portfolio holdings and past returns. Finer data confirm that institutions are frequently the marginal trader and are often on both sides of a trade.[2]

We examine a broad range of institutions and employ a methodology that reveals complex patterns in institutional trading. We investigate changes in the quarterly portfolio holdings of pension funds, mutual funds, investment advisors, insurance companies, commercial banks and trusts, investment banks and brokers, and colleges and foundations. Our methodology separates changes in quarterly portfolio holdings into (1) the initiation of a new position in a stock (entry), (2) the termination of a previous position in a stock (exit), and (3) other additions to or reductions in existing positions (adjustments to ongoing holdings). This decomposition links our empirical work to theoretical models such as Hong and Stein (1999), in which entry and exit decisions convey more information than adjustments to ongoing holdings because of constraints on short sales.

[2] Internal analysis of audit trail data by the NYSE Research Department indicates that in May 2000 (the most recent month for which figures are available), institutional investors accounted for 64 percent of all order flow. The remainder is accounted for as follows: individual investors (4 percent), broker-dealers (27 percent), floor-entered orders (3 percent), and unidentified (2 percent). We are grateful to George Sofianos for providing this information.

Our data consist of the quarterly equity holdings of 1,200 institutions that filed a 13-F statement with the SEC from the third quarter of 1987 through the third quarter of 1995. These holdings represent approximately 6.7 million portfolio positions and an equity market value of $1.8 trillion toward the end of our sample period. We follow Grinblatt et al. (1995) and measure momentum trading as the cross-product of lagged returns and changes in each institution's portfolio weights. We detect only modest evidence of momentum trading over our sample period. The average cross-product of changes in portfolio weights and one-quarter (one-year) lagged returns is five (seven) basis points. This implies that, on average, the returns on stocks held by institutions at the end of a quarter are only five basis points higher than on stocks held at the beginning of the previous quarter.

The decomposition of changes in holdings into entry, exit, and adjustments to ongoing holdings produces a richer set of results. Entry and exit together account for almost 25 percent of all changes in portfolio holdings. Institutions initiate positions in a stock after price increases; for entry, the average cross-product of changes in portfolio weights and one-quarter (one-year) lagged returns is 0.26 percent (1.2 percent). Institutions also terminate previous positions in a stock after price increases; for exit, at the one-quarter (one-year) horizon, the average cross-product is −0.13 percent (−0.83 percent). Thus, institutions act as momentum traders when they initiate new positions in a stock and as contrarian traders when they terminate previous positions in a stock. For adjustments to ongoing holdings, the average cross-products are −0.08 percent for the one-quarter horizon and −0.31 percent for the one-year horizon.

Entry and exit are concentrated in the shares of small firms with high return volatility, while adjustments to ongoing holdings are more common in the shares of larger firms. The proportion of the dollar value of an institution's portfolio devoted to entry is positively related to lagged returns. These results are consistent with the predictions of the Hong and Stein (1999) model. Hong and Stein introduce the notion of a "momentum cycle," which they define as the period of positive return autocorrelation subsequent to the arrival of news. Traders who initiate a position in a stock early in the momentum cycle generate positive profits from continued upward price momentum, while late entrants suffer losses due to price reversals following the cycle. Thus, the profitability of momentum trading is related to the trader's ability to time entry and exit. Lee and Swaminathan (2000) note that the turning point between momentum and reversal is not easily determined ex ante and empirically confirm that late-cycle momentum trading generates negative profits. If institutions invest at different points in the momentum cycle, then entry-to-exit returns should be equal to zero, on average. This is precisely the result that we observe—average entry-to-exit excess returns are close to zero for all holding periods of up to six quarters, and the distribution of momentum traders in the early and late stages of the cycle is essentially uniform.

Such diversity in trading behavior is also evident when we examine the portfolios of different types of institutions. The sensitivity of changes in holdings to past returns is significantly higher for investment advisors and mutual funds than for pension funds and banks. This is particularly important because investment advisors and mutual funds represent two of the largest sectors of the active money management industry and are the most widely studied. Further, when we classify institutions by their investment styles, we find that growth and growth-and-value institutions are momentum traders, but that institutions following value-based strategies are contrarian.

Our results are relevant for the literatures on both institutional trading and asset pricing. Given the extremely small correlation between changes in holdings and lagged returns at the portfolio level, there appears to be little reason to view institutional trading as generally destabilizing to asset prices. Our results also suggest that focusing on particular subsets of institutions provides an incomplete view of the trading landscape, accounting at least in part for the apparent differences in results documented by other studies. For example, Gompers and Metrick (2001) find no evidence of momentum trading using changes in firm-level institutional ownership, because momentum trading by mutual funds is offset by contrarian trading by other institutions. From an asset pricing perspective, the large cross-sectional variation in trading behavior lends itself to alternative interpretations. On the one hand, Hong and Stein (1999, p. 2167) argue that "such heterogeneity cannot be understood in the context of the standard rational model, where there is only one correct style, that which processes all available information in an optimal fashion." On the other hand, a set of traders following a particular (destabilizing) investment strategy should, in a rational world, create arbitrage opportunities that elicit an offsetting investment style. We document precisely such variation in investment styles.

The paper proceeds as follows. Section I discusses the data and sample construction. Section II explores various ways to measure momentum trading. Section III presents empirical results. Section IV discusses robustness issues and additional results. Section V concludes.

I. Data and Sample Construction

Our holdings data come from filings by institutions under Section 13-F of the Securities and Exchange Act of 1934. We provide a brief description of these rules and procedures below. A more complete description of regulations can be found in Lemke and Lins (1987).

A. Reporting Requirements

Section 13-F stipulates that all investment managers with discretion over 13-F securities worth $100 million or more must report their holdings to the SEC at the end of each quarter. Thirteen-F securities include common stock, preferred stock, and convertible debt. The SEC's definition of investment managers includes banks, investment advisors (both domestic and foreign), nonprofit institutions, investment companies, pension funds, colleges and foundations, insurance companies, broker-dealers, and investment banks. State pension funds are not required to file 13-F statements, but some, such as CalPERS, do so voluntarily. Investment discretion is generally defined as the *de jure* or *de facto* power to buy or sell securities. It is important that the power of security selection be vested with the institution, because our interest is in the relation between trading by institutions and past-period returns. When two or more investment managers share investment discretion, only one manager reports holdings to the SEC. Despite efforts to relate reporting requirements to investment discretion, aggregation can add noise to the measurement of trading behavior, particularly for mutual funds. For example, all the holdings of Fidelity's individual mutual funds are aggregated and reported under Fidelity Management and Research. The portfolio managers of the various individual mutual funds under the Fidelity umbrella might exercise investment discretion and pursue different investment styles, but 13-F reporting requirements do not capture this distinction.

B. Sample Construction

We obtain quarterly institutional holdings for all NYSE, AMEX, and Nasdaq firms from the third quarter of 1987 through the third quarter of 1995. These data are collected by CDA Investment Technologies under an agreement with the SEC. CDA, in turn, provides these data to Compact Disclosure, whose CDs we use to extract a security identifier, the number of shares of each firm held by each institution, and the net number of shares bought or sold by the institution over that quarter. Our sample consists of approximately 6.7 million such quarterly portfolio positions reported by 1,200 institutions.

We match the reconstructed portfolio composition database with prices, market values, and returns from the CRSP databases. We search the entire CUSIP history on CRSP to reconcile discrepancies between the two databases.

C. Data Checks and Adjustments

We first verify the accuracy and consistency of the data by comparing the reported changes in holdings with the changes in holdings inferred from successive end-of-quarter positions. Approximately 1 percent of the mismatches are due to rounding errors. Another 10 percent of the mismatches are due to stock splits and related distributions. We confirm the distributions using CRSP factor adjustments and adjust the data accordingly. When institutions file a 13-F statement after the required 45-day period, we backfill their holdings using corrected filing dates. For each institution, we drop the first and last quarter of our time series to avoid artificially introducing entry and exit into the portfolios. Finally, we eliminate involuntary exits due to mergers, consolidations, and bankruptcies as identified by CRSP delisting codes.

A bias may result from the reporting format employed by Compact Disclosure. If more than 250 institutions own a stock, Compact Disclosure reports only the holdings of the largest 250 institutions. The (smaller) holdings of the remaining institutions are summed and reported as an aggregate, thereby inducing an upward bias in our estimates of entry and exit.[3] The original CDA data do not suffer from this aggregation problem. We perform a number of checks to assess the impact of this aggregation. First, we use the original CDA tapes from the last quarter of each calendar year to calculate the percentage of firms in which institutional holdings are aggregated. Less than three percent of the firms in each quarter are affected by the aggregation. Second, we purchase original CDA data for the third quarter of 1991 to determine the magnitude of the upward bias in entry and exit. The percentages of portfolio revisions representing entry and exit for these quarters in the original CDA data are 10.5 percent and 9.1 percent. Corresponding estimates using the Compact Disclosure data are 10 percent and 8 percent, respectively. This suggests that the magnitude of the upward bias is not large. Third, we recalculate our results in two subsamples that are free of the aggregation bias: (1) a subsample formed after eliminating all firms with any aggregated holdings, and (2) a subsample from original CDA data without the aggregation (the last quarter in each of the eight years). The results are similar to those reported in the paper.

II. Measuring Momentum Trading

A. The Basic Measure

We follow Grinblatt et al. (1995) and define a portfolio weight w_{ijt} (the weight in stock i for institution j at time t) as

$$w_{ijt} = \frac{P_{it} H_{ijt}}{\sum_{i=1}^{N} P_i H_{ijt}}, \tag{1}$$

where P_{it} is the end-of-quarter price of stock i at time t and H_{ijt} is the number of shares held by institution j in stock i at time t. A portfolio adjustment is then simply a change in the portfolio weight from $t - l$ to $t(w_{ijt} - w_{ijt-l})$. However, a portfolio weight can change over successive periods due to either a change in holdings or a change in the price of the security. Grinblatt et al. (1995) refer to the latter as passive momentum. Since our interest is in momentum *trading*, we adjust for this passive momentum by calculating both end- and beginning-of-quarter portfolio weights with the same price. We use an end-of-quarter price for this normalization, but average prices produce similar results. Our basic momentum measure,

[3] Compact Disclosure informs us that they apply this aggregation rule due to a data storage constraint at the firm level. Most of the time, the cutoff point is 250 institutions per firm. Although it can sometimes vary between 240 and 260, it *never* drops below 240.

$ITM_{jt}(k,l)$, is simply the sum of the cross-products of individual security weight changes with returns. Specifically,

$$ITM_{jt}(k,l) = \sum_{i=1}^{N} (w_{ijt} - w_{ijt-l})(R_{i,t-k} - R_{m,t-k}), \tag{2}$$

where $R_{i,t-k}$ is a holding-period return for stock i, $R_{m,t-k}$ is the holding-period return for the S&P 500, l indicates the time frame over which the portfolio weight changes are measured, and k indicates the duration over which the corresponding lagged returns are measured. Since the weights in equation (2) at $t - l$ and t are evaluated at the same end-of-quarter prices, they differ from each other only because of active trading.

When l equals one, the weight changes are measured over successive quarters. When l equals two or four, the weight changes are measured over six-month or one-year intervals, respectively, permitting us to examine portfolio revisions involving trading strategies that take more than a quarter to execute. We present results only for quarterly portfolio weight changes or l equal to one; results using l equal to two or four are available upon request. By varying k, we are able to examine the importance of different prior-period return horizons on the decision to change portfolio holdings. We allow k to take on values of zero, one, two, and four, corresponding to current-quarter returns and one-quarter, two-quarter, and four-quarter lagged returns, respectively. The two- and four-quarter lagged returns are six-month and one-year holding-period returns. Our choice of k is motivated by Jegadeesh and Titman (1993) who form momentum portfolios after conditioning on three-, six-, nine-, and 12-month lagged returns. When k equals zero, we cannot distinguish between institutions trading on intraquarter price changes and the price impact of their trades. There are no such interpretation issues when k is greater than zero, and we focus our attention on these estimates.

B. Methodological Issues and Alternatives

The measure in equation (2) produces an estimate for each institution in each quarter and allows us to examine variations in momentum trading over time, across different types of institutions, and across different holding periods. The measure is easy to interpret, because a positive (negative) value implies momentum (contrarian) trading.

The quarterly changes in portfolio holdings represent transactions of varying intensity, including the entry and exit of firms into and out of the portfolio. Entry and exit can distort the basic momentum measure. Consider an institution that owns 1,000 shares in security i_1 and zero shares in security i_2 at the beginning of the quarter. Assume that the price of each security is \$1. The beginning-of-quarter portfolio weights for these securities are one and zero, respectively. If this institution then purchases 500 shares in security i_1 and 1,000 shares in security i_2, the resulting portfolio weights are 0.6 and 0.4, respectively. Even though the institution added to its holdings of security i_1, its portfolio weight in that security declined because of the entry of a new security into the portfolio. A similar distortion in weights occurs when an institution terminates its position in a security.[4]

From one perspective, a negative weight change in security i_1 is appropriate because a smaller proportion of new funds are placed in i_1, relative to a strategy that rebalances holdings to maintain a status quo in weights. However, we wish to measure incremental trading per se, rather than weight changes induced by price movements or entry/exit. Therefore, we separate portfolio changes into three groups: entry, exit, and adjustments to ongoing holdings. We then compute the momentum measure separately for each group. Thus, for entry (exit), the momentum measure is the same as in equation (2), but we only sum weight changes when $w_{ijt-l} = 0$ ($w_{ijt} = 0$). Since the weights no longer sum to one, the sum of the weight changes is nonzero. Thus, weight changes for entry (exit) are always positive (negative). However, since the other term in the cross-product is excess returns, which can be positive or negative, the momentum measure for each component should approach zero under the null hypothesis of no momentum (or contrarian) trading.

C. An Alternative Measure

Our second approach to measuring momentum trading bypasses the distortions to momentum estimates described above. We start by defining a portfolio adjustment in stock i, for institution j at time t, as

$$HRatio_{ijt} = \frac{H_{ijt}}{H_{ijt-l}}. \tag{3}$$

Thus, *HRatio* reflects the (gross) percentage increase or decrease in holdings. Buys correspond to *HRatio* > 1 and sells to *HRatio* < 1. *HRatio* is not defined for entry (*HRatio* $= \infty$), but it is easily isolated because H_{ijt-l} is equal to zero. For exit, *HRatio* is equal to zero. We isolate changes in holdings that constitute entry and exit and assign all buy and sell changes to the groups listed below:

[4] We assess the frequency with which such distortions appear in our data by counting the number of times the weight change for a security is positive even though the institution sold shares and the number of times the weight change for a security is negative even though the institution bought shares. We then add these values together, divide by the total number of securities in the portfolio, and average across all institution-quarters. The resulting ratio represents the average percentage of portfolio weight changes that are affected by entry and exit. For the entire sample, this number is 0.21, implying that 21 percent of all portfolio weight changes are affected by entry and exit.

Buy Quartiles	Sell Quartiles
1. Low-buy ($1.1 \geq HRatio > 1$)	1. Low-sell ($1 > HRatio \geq 0.9$)
2. Med-buy ($1.3 \geq HRatio > 1.1$)	2. Med-sell ($0.9 > HRatio \geq 0.7$)
3. High-buy ($HRatio > 1.3$)	3. High-sell ($0.7 > HRatio$)
4. Entry	4. Exit

Each group represents an increasing level of trading intensity. For example, the low-buy group represents changes of up to 10 percent of the beginning-of-quarter holdings, while the high-buy group represents changes in holdings greater than 30 percent. We also isolate positions in which there is no change in holdings in the quarter ($HRatio = 1$). We refer to the eight buy/sell groups as buy and sell quartiles, despite an unequal number of observations in each group. The predetermined cutoffs preserve a sufficiently large number of observations in each group and provide symmetry in the magnitude of portfolio revisions for both buys and sells.

HRatio allows us to parsimoniously characterize changes in holdings and does not suffer from measurement problems caused by entering and exiting securities. Since the ratio uses only the change in the number of shares over the quarter, there are no passive momentum effects caused by changing prices. Also, the influence of the small upward bias in entry and exit caused by aggregation in our data source (when more than 250 institutions hold shares in a particular firm) is minimized by *HRatio* because, at worst, it causes a misclassification from the high-buy (high-sell) to the entry (exit) group. To determine if changes in holdings are due to momentum trading, we compute average excess returns for all portfolio revisions in a quartile.[5] Since quartile formation takes place across all portfolio revisions in a particular quarter, it is useful to view each quartile as representing trading intensity in one "giant" institutional portfolio. Therefore, we use *HRatio* quartiles to assess momentum within institutional portfolios rather than across types of institutions.

III. Empirical Results

A. Sample Characteristics

Table I shows fourth-quarter averages of the number of reporting institutions, the number of securities in an institution's portfolio, and the dollar value of an institution's portfolio. As expected, the data show a monotonic increase in the average value of institutional portfolios over the sample period, from $988 million in the last quarter of 1987 to $1,598 million by the last quarter of 1994. This monotonic increase remains even after we deflate

[5] The same security can appear multiple times in the calculation of average excess returns, since different institutions can hold (and revise their holdings) in the same stock. This lack of independence does not bias estimates, because it is exactly the type of phenomena we are attempting to capture and it is not due to a regression error. If two institutions purchase a security that went up in price in the prior quarter, both portfolio revisions represent momentum trading and are detected by both the *ITM* and *HRatio* methods.

Table I

Descriptive Statistics of Institutional Portfolios

The table presents descriptive statistics for all institutions that filed a 13-F statement with the SEC during the sample period. To file with the SEC, the reporting institution must manage at least $100 million in equity securities. Dollar values are calculated using the average of beginning- and end-of-quarter prices and are reported in millions of dollars. The CPI series is used to report figures in constant 1987 dollars. All statistics are from the fourth quarter of each calendar year.

	Number of Reporting Institutions	Average Number of Securities in Portfolio	Average Portfolio Value	
			Nominal Dollars	Constant 1987 Dollars
1987	888	171	988	988
1988	902	174	1,078	1,035
1989	941	178	1,293	1,185
1990	970	170	1,234	1,073
1991	1,065	171	1,450	1,209
1992	1,084	185	1,597	1,293
1993	1,128	193	1,734	1,363
1994	1,146	192	1,598	1,225

nominal dollar values by the All Urban Consumers CPI series. The increase in portfolio values is accompanied by an increase in the number of reporting institutions (from 888 in the fourth quarter of 1987 to 1,146 to the fourth quarter of 1994), as more institutions meet the constant $100 million reporting threshold.[6]

Table II shows the frequency and dollar value of entry and exit. We divide the number of firms that enter (exit) an institution's portfolio during the quarter by the number of firms in the portfolio at the beginning of the quarter and analogously divide the dollar value of securities that enter (exit) a portfolio by the dollar value of the beginning-of-quarter holdings. Table II reports averages of these four ratios in each calendar year and the average across all institution-quarters.

The results show that the number of firms in which institutions initiate (terminate) positions is approximately 14 percent (13 percent) of the number of firms in which they hold positions at the beginning of the quarter.[7] The

[6] The number of institutions reported in Table I differs slightly from those reported in Gompers and Metrick (2001) because of two data filters that we apply. As noted in Section I.C, we backfill and correct the original data when institutions report their filings late, and we drop the first and last time an institution appears in our sample. The former results in an increase in the number of institutions in each quarter, relative to Gompers and Metrick (2001), while the latter causes a reduction in the number of institutions.

[7] We also examine quarterly cross-sectional averages to determine if there is any seasonality in the data. We find that entry is slightly higher in the first quarter (especially relative to the fourth quarter), but statistical tests of seasonality are unable to reject the null hypothesis of no seasonality.

Table II

Frequency and Magnitude of Entry and Exit

Column (1) shows the average number of firms entering an institution's portfolio during the quarter scaled by the number of firms in the portfolio at the beginning of the quarter. Column (2) shows the average number of firms exiting an institution's portfolio during the quarter scaled by the number of firms in the portfolio at the beginning of the quarter. Column (3) shows the average dollar value of shares purchased in firms entering an institution's portfolio scaled by the dollar value of the portfolio at the beginning of the quarter. Column (4) shows the average dollar value of shares sold in firms exiting an institution's portfolio scaled by the dollar value of the portfolio at the beginning of the quarter. Each variable is averaged across all institutions in a quarter and then across quarters in a calendar year. Due to data availability, averages for 1987 are computed from two quarters (Q3 and Q4) and averages for 1995 are computed from three quarters (Q1, Q2, and Q3). Averages across all 33 quarters appear at the bottom of the table.

	Ratios Based on Number of Firms in Portfolio		Ratios Based on Dollar Value of Portfolios	
	(1) Entry	(2) Exit	(3) Entry	(4) Exit
1987	0.138	0.112	0.082	0.059
1988	0.137	0.124	0.080	0.074
1989	0.138	0.123	0.083	0.074
1990	0.124	0.130	0.073	0.075
1991	0.137	0.119	0.080	0.067
1992	0.141	0.126	0.085	0.072
1993	0.152	0.139	0.090	0.084
1994	0.146	0.143	0.087	0.085
1995	0.151	0.157	0.092	0.112
Average (33 quarters)	0.140	0.130	0.084	0.078

average dollar value of both entry and exit is approximately 8 percent of the beginning-of-quarter portfolio value, implying that in dollar terms, entry and exit together constitute almost 16 percent of all trading activity. Thus, both the frequency and magnitude of entry and exit appear to be economically important.

B. Momentum within Institutional Portfolios

B.1. The ITM Measure

We calculate our first measure of momentum trading, $ITM_{jt}(k,l)$, for each institution's portfolio in each quarter. We use k equal to zero, one, two, and four for the calculations, corresponding to contemporaneous returns and one-quarter, six-month, and one-year lagged returns, respectively. Table III shows means and medians for the momentum measure for the entire portfolio as well as for the three groups: entry, exit, and adjustments to ongoing holdings. In this and future tables, all $ITM_{jt}(k,l)$ momentum estimates are presented as percentages (that is, the estimate is multiplied by 100).

Table III

Institutional Momentum Measures for All Institutions (in Percent)

The table presents means and medians of the momentum measure,

$$ITM_{jt}(k,l) = \sum_{i=1}^{N} (w_{ijt} - w_{ijt-l})(R_{i,t-k} - R_{m,t-k}),$$

where w_{ijt} is the portfolio weight in stock i for institution j at time t, $R_{i,t-k}$ is the holding-period return for stock i, and $R_{m,t-k}$ is the holding-period return for the S&P 500 index. The portfolio weight is calculated as

$$w_{ijt} = \frac{P_{it} H_{ijt}}{\sum_{i=1}^{N} P_{it} H_{ijt}},$$

where P_{it} is the end-of-quarter price of stock i at time t and H_{ijt} is the number of shares held by institution j in stock i at time t. The four return lags correspond to $k = 0$, 1, 2, and 4. The time frame over which portfolio weight changes are measured is one quarter ($l = 1$). The sample consists of all institutional portfolios from the third quarter of 1987 through the third quarter of 1995. T-statistics based on time-series standard errors are below the means. The percentage of the momentum measures that are positive appear in parentheses below the medians.

	Entire Portfolio		Entry		Exit		Adjustments to Ongoing Holdings	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
$ITM_{jt}(0,1)$	0.23	−0.00	0.44	0.04	−0.07	−0.00	−0.11	−0.05
	(10.6)	(47.8)**	(7.9)	(60.5)***	(1.8)	(41.7)***	(6.1)	(43.2)***
	Paired t-statistic for difference between ongoing and entry = 35.5							
	Paired t-statistic for difference between ongoing and exit = 2.6							
$ITM_{jt}(1,1)$	0.05	−0.00	0.26	0.02	−0.13	−0.00	−0.08	−0.03
	(2.3)	(47.5)**	(5.4)	(56.5)***	(3.1)	(41.5)***	(5.2)	(45.2)***
	Paired t-statistic for difference between ongoing and entry = 25.3							
	Paired t-statistic for difference between ongoing and exit = 5.8							
$ITM_{jt}(2,1)$	0.06	0.00	0.53	0.06	−0.34	−0.02	−0.14	−0.05
	(1.8)	(50.2)	(7.1)	(60.1)***	(4.9)	(46.0)**	(5.7)	(45.1)***
	Paired t-statistic for difference between ongoing and entry = 32.3							
	Paired t-statistic for difference between ongoing and exit = 12.3							
$ITM_{jt}(4,1)$	0.07	0.03	1.20	0.17	−0.83	−0.05	−0.31	−0.08
	(1.1)	(51.4)	(8.2)	(65.5)***	(7.9)	(41.8)***	(5.8)	(45.1)***
	Paired t-statistic for difference between ongoing and entry = 40.5							
	Paired t-statistic for difference between ongoing and exit = 17.1							

**Significant at the five percent level using a binomial test of percent positive equal to 0.5.
***Significant at the one percent level using a binomial test of percent positive equal to 0.5.

Grinblatt et al. (1995) show that an ordinary t-statistic is technically inappropriate for assessing the statistical significance of these estimates because of changing portfolio weights. However, they appeal to the central-limit theorem and use ordinary t-tests (with standard errors from the entire distribution of estimates), since they are virtually identical to asymptotic z-tests. We follow their lead in reporting t-statistics, but note that estimates across quarters are unlikely to be independent. Therefore, we first calculate cross-sectional means for each quarter and use their distribution (across 33 quarters) to generate standard errors and t-statistics. The t-statistics from this Fama–MacBeth-type approach are more conservative than the ordinary t-statistics used by Grinblatt et al. We also report the percentage of positive estimates and use binomial tests to assess their statistical significance. Finally, we show paired t-statistics for the difference in means between entry and changes to ongoing holdings as well as between exit and changes to ongoing holdings.

Table III highlights several important results. For the entire portfolio, the average momentum estimate is positive and statistically significant across all return lags, but the magnitude is quite small. For one-quarter lagged returns ($k = 1$), the average value of $ITM_{jt}(k,l)$ is only 0.05 percent per quarter, implying that, on average, stocks held by institutions at the end of a quarter had returns over that quarter that were only five basis points higher than the corresponding returns on stocks held at the beginning of the previous quarter. In contrast, Grinblatt et al. (1995) find that the momentum estimate for mutual funds over the same horizon is 0.3 percent, six times as large. Moreover, the distribution of our estimates is skewed. Median values are significantly smaller than the mean and, in two cases, are negative. Even though the average momentum *estimate* is slightly positive, the average institution appears to be slightly contrarian.

Perhaps this result is not surprising. After all, our sample encompasses a large number of institutions, and, for every buyer, there must be a seller. If institutions generally trade with each other, the market-clearing condition implies that estimates of aggregate momentum trading must be close to zero. However, if institutions trade with individuals and/or other institutions, then aggregating all institutions would account for the lack of economically significant momentum trading.[8] Regardless, the small magnitude of aggregate momentum trading alleviates the concern that institutional trading generally destabilizes stock prices.

The other columns of Table III, which provide separate momentum estimates for entry, exit, and adjustments to ongoing holdings, show striking differences. Both the mean and median momentum measures are small and negative for adjustments to ongoing holdings. For one-quarter lagged returns ($k = 1$), the mean is -0.08 and the median is -0.03. As the return lag increases, the mean estimates increase, but the medians remain small. For

[8] We can never be sure if our sample institutions trade with each other, with individuals, or with other institutions. We can, however, get a general sense of how much trading volume in a stock is accounted for by the institutions in our database. To do so, we sum the change in quarter-to-quarter holdings by all institutions in each firm-quarter and divide this by total trading volume for that firm-quarter. The average of this ratio (across all firm-quarters) is 0.65, implying that our sample institutions account for at least 65 percent of total trading volume.

entry, both the mean and median momentum estimates are positive and substantially larger across all return lags. For one-quarter (one-year) lagged returns, the mean for entry is 0.26 percent (1.20 percent) with a t-statistic of 5.4 (8.2). Paired t-tests easily reject the null hypothesis that the mean for entry is equal to that for adjustments to ongoing holdings. The momentum estimates for exit are uniformly negative and also larger in magnitude than those for the ongoing adjustments group. Using a one-year return lag, the mean for exit (ongoing adjustments) is -0.83 (-0.31) with a t-statistic of 7.9 (5.8). A paired t-test also rejects equality between exit and the ongoing adjustments group (t-statistic = 17.1).

It is interesting to consider the net effect of entry, exit, and adjustments to ongoing holdings on the entire portfolio. Since the momentum estimate for entry is typically larger than that for exit, the effects of net entry/exit are positive and dominate the weak contrarian behavior observed in adjustments to ongoing holdings. Summing the three estimates for one-year lagged returns ($-0.31 + 1.20 - 0.83$) results in an average estimate for the entire portfolio of 0.07, which is clearly driven by the effects of net entry/exit. This result is consistent with Gompers and Metrick (2001), who conclude that once they control for firm size, there is no evidence of (aggregate) momentum trading. Our results suggest that, even unconditionally, this is the case. When momentum matters, it does so at the time of entry.

B.2. The HRatio Measure

We next describe momentum trading using our second measure, *HRatio*. In Panel A of Table IV, we report the number of observations that fall into each of the eight buy/sell *HRatio* groups described in Section II.C, as well as a no-change group. Panel A also shows the average intensity of changes in holdings in each group, calculated as the dollar value of the portfolio revision (the change in the number of shares times the average price) scaled by the beginning-of-quarter portfolio value. The data show a monotonic relation between the intensity of the portfolio revision and the buy/sell quartiles. For example, the average entry (exit) decision represents 0.59 percent (0.56 percent) of the entire portfolio. In contrast, the average low-buy (low-sell) decision represents only 0.02 percent (0.03 percent) of the entire portfolio. This suggests that the primary mechanism by which institutions adjust their portfolios is entry and exit.

In Panel B, we show the average S&P 500-adjusted excess return at various return lags (k = 0, 1, 2, and 4). Next to each return are paired t-statistics that represent tests of differences from the no-change group. The panel shows that across both buys and sells, and regardless of the horizon, prior excess returns are positive. This is consistent with the entry/exit results in Table III in that entry reflects momentum trading, but exit shows contrarian behavior. However, there is dramatic variation in both the returns and the test statistics across the groups. Average returns prior to entry are always statistically and economically larger than the no-change group. As one moves

Table IV

Excess Returns and Security Characteristics by *HRatio* Quartiles

Portfolio revisions, calculated as $HRatio_{ijt} = H_{ijt}/H_{ijt-l}$, are placed in one of nine groups shown below. Panel A shows the number of observations in each group and the average intensity of portfolio revisions in that group. Trading intensity is calculated as the dollar value of the portfolio revision (change in number of shares times the average price), divided by the beginning-of-quarter portfolio value. Panel B shows average returns in excess of the S&P 500 across all portfolio revisions in each group. Panel C shows average security characteristics across all portfolio revisions in a group. Market capitalization is reported in billions of dollars. Volatility is calculated as the standard deviation of daily returns during the quarter. Turnover is calculated as the total quarterly trading volume divided by the number of shares outstanding. Time-series t-statistics based on 33 quarters appear in parentheses and represent tests of differences of each group from the no change group.

	Buy Quartiles				No Change	Sell Quartiles			
	Entry	High-Buy	Med-Buy	Low-Buy		Low-Sell	Med-Sell	High-Sell	Exit
Panel A: Number of Observations									
Number	811,126	560,080	420,986	800,816	1,682,994	838,195	457,454	426,225	715,266
Trading intensity	0.59	0.34	0.10	0.02	0.00	0.03	0.13	0.35	0.56
Panel B: Excess Returns (in Percent)									
$k = 0$	3.44 (2.8)	0.50 (0.2)	0.19 (0.1)	0.44 (0.1)	0.34	0.65 (0.4)	0.95 (0.7)	0.56 (0.2)	−0.26 (0.6)
$k = 1$	2.71 (2.1)	1.68 (1.4)	0.72 (0.5)	0.60 (0.3)	0.27	0.71 (0.5)	1.21 (1.0)	0.81 (0.5)	0.50 (0.2)
$k = 2$	5.43 (3.1)	3.88 (2.3)	2.12 (1.2)	1.43 (0.6)	0.65	1.46 (0.7)	2.54 (1.5)	2.28 (1.1)	1.79 (0.7)
$k = 4$	11.30 (3.9)	9.15 (3.3)	5.81 (2.1)	3.81 (1.0)	1.78	3.52 (0.9)	5.95 (2.1)	6.36 (2.1)	5.22 (1.6)
Panel C: Security Characteristics									
Price ($)	35.5 (2.0)	37.0 (1.3)	37.1 (1.4)	41.0 (0.8)	39.4	44.2 (2.3)	39.7 (0.1)	36.9 (1.3)	33.7 (3.0)
Market cap ($ billion)	2.51 (5.0)	3.44 (15.2)	4.09 (16.6)	5.00 (16.9)	5.85	5.58 (19.8)	4.23 (16.4)	3.03 (11.9)	2.67 (6.9)
% in small cap	53 (6.1)	43 (20.6)	40 (21.5)	37 (22.6)	38	32 (32.1)	36 (28.0)	41 (23.2)	52 (6.2)
% in mid cap	35 (5.1)	38 (11.4)	38 (11.6)	37 (10.1)	31	39 (15.2)	41 (16.8)	43 (18.3)	34 (2.9)
% in large cap	13 (4.8)	19 (22.2)	22 (23.6)	26 (21.9)	31	29 (25.8)	23 (22.7)	16 (13.3)	14 (7.9)
Volatility	0.024 (0.4)	0.022 (1.8)	0.021 (2.6)	0.020 (3.6)	0.025	0.019 (4.2)	0.021 (3.0)	0.023 (1.5)	0.026 (0.6)
Turnover	0.304 (8.9)	0.274 (7.6)	0.235 (3.5)	0.203 (1.1)	0.210	0.197 (2.3)	0.238 (4.0)	0.284 (9.2)	0.298 (10.3)

across the buy quartiles, there is an almost monotonic decline in both average returns and their statistical significance. For example, for the one-quarter lagged return ($k = 1$), the excess return for entry is 2.7 percent and declines monotonically to 0.6 percent for the low-buy group. On the sell side, only 2 of the 16 excess returns are statistically different from the no-change group, and there is no discernible pattern across the quartiles.[9]

These results clearly indicate the source of trading momentum: Entry is associated with the largest lagged returns as well as the greatest portfolio revision intensity. It is possible that entry and exit are concentrated in particular types of securities, and we turn to this next.

B.3. Security Characteristics

In Panel C of Table IV, we show the characteristics of the securities in each of the nine groups. We calculate two measures of firm size: (1) market value at the beginning of the quarter, and (2) the percentage of portfolio revisions in small-cap (less than $1 billion in market value), mid-cap ($1 billion to $5 billion in market value), and large-cap (greater than $5 billion in market value) stocks. We also calculate average volatility (standard deviation of daily returns during the quarter), turnover (total quarterly trading volume scaled by the number of shares outstanding), and price level (as of the beginning of the quarter). Each average is calculated across all portfolio revisions in a quarter and then across quarters.

We start by examining average price levels across the nine groups because large differences in prices could substantially influence our inferences. For example, the formation of the *HRatio* quartiles gives each security equal weight, so that a 10 percent increase in holdings of a stock trading at $10 per share is given the same weight as a 10 percent increase in holdings of a stock trading at $100 per share. Panel C of Table IV shows some differences in price levels; average prices generally decline as portfolio revision intensity increases. However, these differences are quite small. Average prices are in the $30–$40 range and the variation in prices across quartiles is about $5, suggesting that equally weighting the portfolio revisions is not likely to cause any systematic bias in quartile formation.

Differences in other security characteristics across the nine groups are evident. Over 53 percent (52 percent) of all entry (exit) takes place in small

[9] This could be because our benchmark is too small. However, the choice of a benchmark is motivated by our desire to understand trading *behavior* rather than assess risk-adjusted performance. The latter typically motivates the use of multifactor models (see Fama and French (1993) and Carhart (1997)). In contrast, we seek to describe how an institution revises its holdings in a security, conditional on a lagged return. Grinblatt and Keloharju (2000) face a similar dilemma and use raw returns. We could also use raw returns, but our sample period is one of generally rising prices. We use the S&P 500 return as a benchmark, because it is often used to judge money managers' performance. As a robustness check, we employ two other benchmarks and discuss these results in Section IV.

firms. This is consistent with Bennett, Sias, and Starks (2000), who report an increased institutional preference for smaller firms with high risk. For the low-buy (low-sell) group, this percentage declines to 37 percent (32 percent). The decline in firm size from entry (exit) to the low-buy (low-sell) group is monotonic. Not surprisingly, as the percentage of small-cap firms declines across quartiles, the percentage of large-cap firms increases. Similar declines are evident in volatility and turnover.

B.4. Further Evidence on Entry and Exit

The previous section shows that momentum trading takes place primarily through entry. It is possible that this result is simply the artifact of naïve portfolio strategies and/or institutional constraints on investment decisions. Consider, for example, an institution such as an index fund that wishes to hold a value-weighted portfolio of stocks. In the presence of transaction costs, this institution would add stocks to its portfolio when they meet a minimum market capitalization threshold. A price increase obviously causes stocks to meet such a threshold. Other institutional preferences could also independently cause entry to be positively correlated with prior price increases. For example, investment managers constrained by considerations of prudence may be more likely to add securities that have reached a minimum size threshold (see Badrinath, Gay, and Kale (1989) and Del Guercio (1996)). Alternatively, institutional preferences for certain stock characteristics, such as liquidity, may be correlated with past price increases (see Falkenstein (1996)). The fact that entry takes place after price increases is consistent with the above explanations. However, these explanations also require that exit take place after price declines—an effect that we do not observe. This suggests that such simple explanations are, at best, only partly responsible for the entry and exit patterns that we document.

Our results could also reflect the trading behavior described by Hong and Stein (1999). In their model, information diffusion is slower in small stocks, causing positive autocorrelation in prices, and inducing momentum traders to submit buy orders. This is consistent with our evidence that entry takes place in small stocks. Moreover, the intensity of trading should be positively related to the degree of price momentum, and average entry-to-exit profits should be positive.

In Panel A of Table V, we categorize all entry and exit decisions into four quartiles based on two measures of trading intensity. The first measure is the dollar value of the portfolio revision, scaled by the beginning-of-quarter portfolio value; the second measure is the number of shares bought or sold, scaled by the total shares outstanding for that security. Panel A shows the average intensity (using both measures) and average excess returns at various lags for each quartile. The figures for the no-change group are also reported for comparison purposes and paired t-statistics for differences from the no-change group appear in parentheses.

Table V

Entry/Exit Trading Intensity and Entry-to-Exit Returns

In Panel A, all portfolio revisions that constitute entry (exit) are classified into one of four quartiles based on two metrics of trading intensity: (1) the dollar value of the portfolio revision in security i scaled by the dollar value of the entire portfolio at the beginning of the quarter, and (2) the number of shares bought or sold in security i scaled by the number of shares outstanding for that security at the beginning of the quarter. The table shows the mean trading intensity by each metric for all quartiles, followed by average excess returns. For comparison, a column with similar data for no change (i.e., no portfolio revisions) is also shown. Below each mean return is a paired time-series t-statistic of the difference from the no-change group. Panel B shows the average preentry quarter's return and entry-to-exit holding-period returns.

Panel A: Trading Intensity Quartile Returns

	Entry Quartiles				No	Exit Quartiles			
	1 (Low)	2	3	4 (High)	Change	1 (Low)	2	3	4 (High)
Trading intensity quartiles by dollar value									
Intensity	0.003	0.027	0.161	2.018	—	0.003	0.029	0.166	3.811
$k = 0$	3.05	3.70	3.82	3.45	0.34	−0.78	−0.42	−0.16	0.08
	(5.1)	(11.8)	(12.3)	(8.7)		(2.0)	(2.6)	(1.5)	(0.8)
$k = 1$	1.59	2.68	2.98	2.64	0.27	−0.89	0.58	0.96	1.50
	(3.4)	(8.9)	(9.2)	(7.8)		(3.0)	(0.3)	(1.5)	(2.8)
$k = 2$	3.95	5.72	6.10	5.50	0.65	−1.06	2.25	3.04	3.87
	(4.5)	(9.1)	(9.8)	(10.0)		(4.1)	(3.1)	(5.2)	(6.6)
$k = 4$	9.36	12.57	13.09	12.43	1.78	0.12	7.17	8.40	9.48
	(6.3)	(10.4)	(11.8)	(13.5)		(4.9)	(6.2)	(11.7)	(11.2)
Trading intensity quartiles by shares outstanding									
Intensity	0.009	0.039	0.139	1.920	—	0.009	0.040	0.141	1.286
$k = 0$	1.82	2.69	3.68	5.83	0.34	−0.18	−0.38	−0.40	−0.30
	(4.3)	(9.2)	(11.0)	(9.3)		(1.5)	(2.9)	(2.5)	(1.2)
$k = 1$	1.35	1.96	2.84	3.76	0.27	0.61	0.49	0.65	0.39
	(2.5)	(7.0)	(8.7)	(6.7)		(0.8)	(0.2)	(0.4)	(0.3)
$k = 2$	2.79	4.38	6.05	8.07	0.65	1.26	1.70	2.47	2.68
	(4.6)	(9.6)	(8.6)	(7.4)		(1.1)	(2.6)	(3.0)	(1.9)
$k = 4$	7.30	10.42	13.47	16.30	1.78	3.96	5.10	7.37	8.78
	(8.2)	(11.5)	(10.5)	(9.4)		(2.7)	(6.3)	(6.0)	(4.5)

Panel B: Entry-to-Exit Returns

Holding Period (Quarters)	Preentry Quarter Return (%)	Entry-to-Exit Holding-Period Return (%)	% Positive	Number of Observations
1	3.57	−0.91	44.3	133,594
2	3.33	−0.66	44.2	107,124
3	3.24	−0.53	43.7	69,303
4	3.54	0.01	44.1	48,494
5	3.53	0.01	43.4	35,654
6	3.19	1.02	44.6	26,921

Excess returns for entry are systematically positive and generally increase across the quartiles. The quartiles provide a convenient economic interpretation. For example, the fourth entry quartile shows that a 12.4 percent excess return over the prior year ($k = 4$) induces institutions to devote 2 percent of their portfolio to the stock. One way to judge the economic significance of these portfolio revisions is to compare them to the average equally weighted portfolio. As shown in Table I, the average number of securities in institutional portfolios over the entire sample period is 179. This implies equal portfolio weights of 0.56 percent, which suggests that a two-percentage-point adjustment is meaningful. Similarly, by the second measure, a 16.3 percent annual excess return results in institutions buying 1.9 percent of the outstanding shares. Again, 1.9 percent of the outstanding shares represents an economically large block of equity. Consistent with the results in Table IV, the exit quartile excess returns are substantially smaller. Also, in 9 out of 32 cases, the returns are statistically insignificant.

These results are consistent with Hong and Stein's (1999) model. Their model also implies that, on average, momentum trading is profitable. To determine if this is the case, we examine entry-to-exit returns over various holding periods in Panel B of Table V. We restrict the sample to only those cases in which we can clearly identify both entry and exit and calculate the holding period of each stock from the quarter after entry. We then calculate the average preentry quarterly excess return and the entry-to-exit excess holding-period return using the S&P 500 as the benchmark. For the latter, since compounding starts the quarter after entry, the holding-period return does not include the price impact of the trades that go into establishing the portfolio position. We report results for holding periods ranging from one through six quarters.

The results show an average positive preentry return of about 3 percent. This is similar to the preentry return of 3.4 percent in Table IV. The entry-to-exit returns, however, are negative for holding periods from one to three quarters and only marginally positive thereafter. On balance, excess returns are close to zero. Risk adjustments and round-trip transaction costs in these small stocks are only likely to further lower these returns. Although some institutions may profit from trend chasing, momentum trading does not appear to be profitable on average and is at odds with the Hong and Stein (1999) model.

This result is somewhat puzzling, particularly since Jegadeesh and Titman (1993, 2001) show that momentum profits can be quite large. A reconciliation between the two sets of results lies in recognizing that Jegadeesh and Titman base their results on a portfolio approach in which each security is assigned to 1 of 10 return-based portfolios every month. The winner portfolio (referred to as P1) contains securities with the highest returns in the portfolio formation period (which can vary from 3 to 12 months). Similarly, the loser portfolio (P10) contains securities with the lowest returns in the portfolio formation period. The Jegadeesh and Titman (1993) momentum strategy consists of going long in the winner portfolio and short in the loser portfolio.

In the case of institutions, we only observe the long side of the strategy. Therefore, if entry takes place in stocks that are in the P1 portfolio, then entry-to-exit returns should be positive. If entry takes place in both the early and late stages of the momentum cycle (that is, in portfolios P1 through P10), then entry-to-exit returns should be equal to zero. To determine if this is the case, we assign each entry-to-exit observation to portfolios P1 through P10 based on the procedure in Jegadeesh and Titman (1993).[10] We then examine the distribution of these portfolio assignments. We find that approximately 60 percent of the entry-to-exit observations fall in portfolios P1 through P5, but only 12 percent fall in the P1 portfolio. A χ^2 of the null hypothesis of a uniform distribution fails to reject. Evidently, entry takes place in both the early and late stages of the momentum cycle. This is consistent with Lee and Swaminathan's (2000) observation that momentum cycles for individual securities are "far less deterministic" than those for portfolios and suggests that accurately timing these cycles is a difficult undertaking. The fact that the distribution of entry-to-exit returns includes both winners and losers suggests that institutions follow diverse trading strategies. Accordingly, we shift our focus from trading within institutional portfolios (entry, exit, and adjustments to ongoing holdings) to trading behavior across different types of institutions.

C. Momentum Trading across Institutional Portfolios

There are significant differences in the operating environment, incentives, size, investment style, taxation, regulation, and organization of different types of institutions that may be systematically related to trading behavior. We discuss such differences below.

C.1. Factors Influencing Institutional Trading Decisions

Commercial banks manage assets delegated to them from two primary sources, trust accounts and pension plans. Trust assets are subject to "prudent-expert" considerations, which require a tilting of portfolios toward "high-quality" securities (see Badrinath et al. (1989) and Del Guercio (1996)). Pension assets are often managed by investment advisory firms that are, in turn, sometimes owned by commercial banks.

Larger pension funds, colleges, and foundations often manage all or a portion of their assets internally. Since pension funds are subject to the Employees Retirement Income Security Act (ERISA), they too are partially constrained by prudence considerations. Unlike banks, pension funds are permitted to consider the positive effects of portfolio diversification. The assets of pension funds, colleges, and foundations are considered nontaxable. Frequently, pension funds segment their equity portfolios into passive and

[10] We thank Jennifer Conrad and Bob Dittmar for providing these portfolio assignments. They are based on a six-month return for the portfolio formation period.

actively managed segments and employ independent investment advisors to manage the latter segment.

Independent investment advisors and money managers are employed by private and public pension funds, colleges, and foundations, as well as by wealthy individual investors. Investment advisors typically retain investment discretion over the assets delegated to them and are evaluated on a quarterly or annual basis, either by the provider of funds or by outside consultants. Lakonishok et al. (1991) argue that the quarterly or annual evaluation of investment advisors can cause them to engage in window dressing (i.e., selling losers at the end of the evaluation period). Lakonishok, Shleifer, and Vishny (1992b) argue that the structure of the money management industry is fraught with agency problems and that these agency problems explain the relative underperformance of investment advisors.

The assets of mutual funds originate largely from individual investors. Therefore, they are not influenced by prudence considerations. Unless they are in 401K or IRA accounts, they are not tax exempt. Individuals do not monitor mutual fund performance in the same way that pension funds monitor investment advisors. However, individuals can redeem their shares on demand, thereby influencing the relation between asset flow and performance (see, e.g., Sirri and Tufano (1998)). Del Guercio and Tkac (1998) examine differences in this relation for both mutual and pension funds and find that mutual fund flows are related to raw returns and pension fund returns are related to performance relative to the S&P 500.

Unlike other types of institutions, funds invested by insurance companies are not delegated to them by other institutional or individual investors. Insurance company portfolio managers are not subject to oversight and regular evaluation by policyholders. Badrinath, Kale, and Ryan (1996) note that safety-net considerations under a model investment law prescribed by the National Association of Insurance Commissioners (NAIC) explain only a small portion of the cross-sectional dispersion in insurance company equity holdings.

Trading decisions can also be influenced by the investment style of the institution. Many institutions offer several investment vehicles (accounts or funds) that use different investment styles. For example, an investment advisor might offer an investment vehicle that follows a value-based strategy or another vehicle that invests based on earnings momentum. Still others offer diversified investment products that mimic the performance of market indices.

In addition to differences in regulation, institution type, and investment style, the level of an institution's holdings in a particular security and/or subgroup of securities can also play an important role in trading decisions. For instance, insurance companies are prohibited from investing more than 10 percent of their assets in any one security. The ownership of more than 5 percent of a firm's stock automatically triggers additional reporting requirements for all institutions. Also, as the size of an institution's position in a particular security becomes larger, the cost of trading that block in the future is likely to increase. As the dollar volume of assets under management increases, these constraints could force some institutions to invest incremental assets in smaller and perhaps riskier securities (Bennett et al. (2000)).

C.2. Institution Classification Procedures

We manually match each institution in our sample with a textual description of the institution from the *Money Market Directory of Pension Funds and their Investment Advisors* (1990 to 1995), *Weisenberger Investment Companies' Yearbook* (1992 to 1995), and *Nelson's Directory of Investment Managers* (1988 to 1995). Based on these descriptions, each institution is classified into one of the following categories: commercial banks and trusts, colleges and foundations, investment banks and broker-dealers, insurance companies, money managers and investment advisors, mutual funds, corporate and public pension funds, and others. Our classifications are finer than those provided by CDA in that we break out pension funds, investment banks and broker-dealers, and colleges and foundations (CDA classifies these as others).

We use data purchased from the publishers of the *Money Market Directory of Pension Funds and Their Investment Advisors* to attribute an investment style to each institution. For each institution covered by the *Money Market Directory*, the data show yes/no responses to a list of 18 style classifications. As many of these classifications are similar in spirit, we collapse the responses into four broad style categories:

1. Growth: Institutions that identify their style as one characterized by consistent growth and/or earnings momentum.
2. Value: Institutions that identify their styles as some combination of low P/E, contrarian, yield, bottom-up, or fundamental strategies.
3. Growth and value: Institutions that identify their styles as characterized by some combination of growth and value strategies.
4. Diversified/miscellaneous: Institutions that manage multiple funds with different investment styles, and also those that follow indexing strategies.

Details of the institution type and investment style classification procedures are available upon request.

C.3. Momentum Trading and Types of Institutions

In Table VI, we report estimates of our momentum measure $ITM_{jt}(k,l)$ by institution type for all return lags (all values of k). The table is separated into Panel A for entry, Panel B for exit, and Panel C for adjustments to ongoing holdings. Each panel contains equal-weighted means, time-series t-statistics, and the percentage of positive momentum measures.

For entry (Panel A), the average momentum measures are positive and statistically significant across all types of institutions and all return lags. While the results clearly show momentum trading by all types of institutions, when new securities are added to their portfolios, there is considerable variation in the estimates. The largest estimates are for mutual funds. These are followed by two clusters. Investment banks and brokers, insurance companies, and money managers and investment advisors form one cluster, in which average momentum estimates are just below those for mutual funds (for one-year lagged returns, the estimates are around 0.65 percent). Banks, colleges and foundations, and pension funds form another cluster, with substantially lower estimates of momentum trading (for one-year lagged returns, these estimates cluster around 0.18 percent).

For exit, Panel B shows that across all return lags and all types of institutions, 23 of the 28 mean estimates are negative. Once again, there is considerable cross-sectional variation, with clusters forming around exactly the same types of institutions as for entry. Momentum estimates for exit are somewhat smaller than those for entry. Although we do not report them in the table, net entry/exit estimates are uniformly positive. Changes in ongoing holdings show some momentum behavior for commercial banks, investment banks, and insurance companies, and contrarian behavior for the remaining types of institutions; 19 of the 28 estimates (across all return lags and all institution types) are negative. Consistent with the results in Table III, the momentum estimates for the ongoing adjustments group are substantially smaller than those for entry and exit.

C.4. Momentum Trading and Investment Styles

Table VII shows estimates of momentum trading for institutions classified by the four investment style categories. Panel A shows estimates for entry, Panel B shows estimates for exit, and Panel C contains estimates for adjustments to ongoing holdings.

Entry (Panel A) shows evidence of momentum trading across all return lags for institutions following diversified, growth, and growth-and-value investment styles. There is no evidence that institutions that follow value strategies add securities to their portfolios after price run-ups; two of the estimates are positive and two are negative, but all four are extremely small. Exit (Panel B) shows evidence of contrarian behavior across all investment styles, although once again, the magnitude of contrarian trading is smallest for value traders. For the ongoing adjustments group (Panel C), the estimates are small and close to zero for all investment styles except value, for which the average estimates are large and negative across all four return lags.

In general, the estimates are consistent with these institutions' stated investment styles. Across all return lags, F-tests easily reject the null hypotheses that the estimates are equal across institution type (Table VI) and across investment style (Table VII).

IV. Robustness Issues and Additional Results

As a robustness check, we use a buy-sell decomposition of $ITM_{jt}(k,l)$ that follows Grinblatt et al. (1995). We use partial sums in equation (2), where for buys (sells), the summation only takes place when $w_{ijt} > w_{ijt-l}$ ($w_{ijt} < w_{ijt-l}$), and instead of subtracting a market return, we subtract the mean

Table VI

Institutional Momentum Measures by Institution Type (in Percent)

The table presents means of the momentum measure,

$$ITM_{jt}(k,l) = \sum_{i=1}^{N} (w_{ijt} - w_{ijt-l})(R_{i,t-k} - R_{m,t-k}),$$

for institutions with each investment style from the third quarter of 1987 to the third quarter of 1995. The four return lags correspond to k = 0, 1, 2, and 4. The time frame over which portfolio weight changes are measured is one quarter (l = 1). The momentum measure is calculated separately for entry, exit, and adjustments to ongoing holdings. T-statistics are based on time-series standard errors.

	$ITM_{jt}(0,1)$			$ITM_{jt}(1,1)$			$ITM_{jt}(2,1)$			$ITM_{jt}(4,1)$		
	Mean	t	% Pos	Mean	t	% Pos	Mean	t	% Pos	Mean	t	% Pos
Panel A: Entry												
Commercial banks and trusts	0.09	4.0	60***	0.07	3.7	56***	0.16	5.0	61***	0.40	5.7	67***
Colleges and foundations	0.08	1.4	54**	0.06	2.5	55***	0.17	3.7	59***	0.60	2.4	64***
Investment banks and brokers	0.47	4.1	61***	0.30	3.1	60***	0.65	4.9	62***	1.32	5.9	69***
Insurance companies	0.34	7.7	63***	0.21	5.2	58***	0.43	6.5	64***	0.97	7.2	69***
Money mgrs. and inv. advisors	0.58	7.5	61***	0.34	5.1	58***	0.70	6.8	59***	1.56	8.4	64***
Mutual funds	0.60	7.6	64***	0.39	5.9	60***	0.82	6.8	64***	1.80	9.3	71***
Pension funds	0.02	0.5	56***	0.01	0.4	57***	0.01	0.3	61***	0.30	3.7	66***
F-statistic (p-value) for equality of $ITM_{jt}(k,l)$		42.8 (0.00)			22.9 (0.00)			33.9 (0.00)			54.0 (0.00)	

Panel B: Exit												
Commercial banks and trusts	−0.05	2.6	48	−0.04	2.3	47**	−0.08	3.7	44***	−0.22	5.8	41***
Colleges and foundations	−0.10	4.2	43***	−0.03	1.7	53**	−0.08	2.2	47**	−0.19	2.9	52
Investment banks and brokers	−0.14	2.0	44***	−0.14	1.8	49	−0.35	2.9	45***	−0.87	4.5	39***
Insurance companies	−0.00	0.1	52	−0.11	0.3	47**	−0.28	5.2	44***	−0.70	7.5	39***
Money mgrs. and inv. advisors	−0.07	1.4	50	−0.16	2.7	49	−0.45	4.5	46***	−1.11	7.2	43***
Mutual funds	−0.03	0.6	48	−0.20	3.5	47**	−0.44	5.3	43***	−1.21	9.8	35***
Pension funds	−0.07	1.9	40***	−0.01	0.5	46***	−0.04	2.4	42***	−0.17	2.4	40***
F-statistic (p-value) for equality of $ITM_{jt}(k,l)$	27.4 (0.00)			7.19 (0.00)			18.5 (0.00)			36.3 (0.00)		
Panel C: Adjustments to Ongoing Holdings												
Commercial banks and trusts	−0.05	4.0	45***	−0.03	3.0	47**	−0.06	3.2	48	−0.09	3.3	49
Colleges and foundations	−0.18	3.3	36***	−0.04	1.3	44***	−0.03	0.5	46***	−0.03	0.3	46***
Investment banks and brokers	−0.19	4.2	42***	−0.10	1.8	44***	−0.14	1.6	45***	−0.13	1.4	48
Insurance companies	−0.04	1.4	47**	−0.01	0.3	46***	−0.11	2.3	45***	−0.23	3.3	42***
Money mgrs. and inv. advisors	−0.12	5.0	42***	−0.12	5.0	45***	−0.20	4.7	44***	−0.45	5.4	44***
Mutual funds	−0.10	3.4	41***	−0.06	1.6	45***	−0.13	2.5	43***	−0.33	3.0	43***
Pension funds	−0.16	5.4	36***	−0.05	1.5	40***	−0.15	3.3	40***	−0.17	2.4	43***
F-statistic (p-value) for equality of $ITM_{jt}(k,l)$	4.2 (0.00)			2.7 (0.01)			2.7 (0.01)			6.4 (0.00)		

**Significant at the five percent level using a binomial test of percent positive equal to 0.5.
***Significant at the one percent level using a binomial test of percent positive equal to 0.5.

Table VII

Institutional Momentum Measures by Investment Style (in Percent)

The table presents means of the momentum measure,

$$ITM_{jt}(k,l) = \sum_{i=1}^{N}(w_{ijt} - w_{ijt-l})(R_{i,t-k} - R_{m,t-k}),$$

for institutions with each investment style from the third quarter of 1987 to the third quarter of 1995. The four return lags correspond to k = 0, 1, 2, and 4. The time frame over which portfolio weight changes are measured is one quarter (l = 1). The momentum measure is calculated separately for entry, exit, and adjustments to ongoing holdings. T-statistics are based on time-series standard errors.

	$ITM_{jt}(0,1)$			$ITM_{jt}(1,1)$			$ITM_{jt}(2,1)$			$ITM_{jt}(4,1)$		
	Mean	t	% Pos	Mean	t	% Pos	Mean	t	% Pos	Mean	t	% Pos
Panel A: Entry												
Diversified/misc.	0.48	6.0	62***	0.22	4.1	56***	0.46	4.6	60***	1.12	7.0	66***
Growth only	0.66	5.1	66***	0.48	4.1	60***	0.86	4.6	66***	1.74	5.9	75***
Growth & value	0.65	8.1	66***	0.43	5.8	61***	0.90	7.3	66***	1.87	8.9	73***
Value	0.03	1.1	47**	−0.04	1.1	42***	−0.06	0.3	44***	0.19	1.6	48
F-statistic (p-value) for equality of $ITM_{jt}(k,l)$	40.6 (0.00)			39.1 (0.00)			48.3 (0.00)			56.0 (0.00)		

Panel B: Exit												
Diversified/misc.	−0.09	1.7	49	−0.24	3.7	47**	−0.56	5.6	43***	−1.13	7.4	39***
Growth only	−0.07	1.1	51	−0.16	1.7	48	−0.34	3.3	44***	−0.88	4.3	38***
Growth & value	0.03	0.5	53***	−0.13	2.3	51	−0.44	4.3	46***	−1.18	7.4	41***
Value	−0.18	3.7	41***	−0.11	2.6	45***	−0.17	2.4	45***	−0.25	2.6	46***
F-statistic (p-value) for equality of $ITM_{jt}(k,l)$	12.8 (0.00)			2.2 (0.05)			6.3 (0.00)			17.8 (0.00)		
Panel C: Adjustments to Ongoing Holdings												
Diversified/misc.	−0.11	2.7	44***	−0.06	2.4	46***	−0.14	3.3	46***	−0.32	3.7	44***
Growth only	−0.08	1.1	50	−0.05	0.9	51	−0.03	0.3	50	−0.14	0.7	47**
Growth & value	0.04	1.7	46***	−0.05	1.7	50	−0.06	1.3	49	−0.28	2.9	49
Value	−0.33	14.1	30***	−0.27	9.8	31***	−0.39	8.4	33***	−0.66	7.6	33***
F-statistic (p-value) for equality of $ITM_{jt}(k,l)$	21.4 (0.00)			12.7 (0.00)			15.0 (0.00)			6.3 (0.00)		

**Significant at the five percent level using a binomial test of percent positive equal to 0.5.
***Significant at the one percent level using a binomial test of percent positive equal to 0.5.

return over the subsequent four quarters. We calculate these buy and sell $ITM_{jt}(k,l)$ measures quarterly for each institution. The results are less sharp than *HRatio* because of the mixing of entry/exit with adjustments to ongoing holdings, but, in general, the patterns are similar to those reported in the paper.

We also check the robustness of our momentum results using alternative return benchmarks. We use the CRSP value-weighted index to calculate excess returns and obtain results similar to those reported in the paper. We next use an in-sample benchmark that is an equally weighted return of all securities in which institutions hold positions in that quarter. This benchmark reduces excess returns for all *HRatio* quartiles. For example, for a one-quarter return lag ($k = 1$), average preentry (preexit) excess returns fall from 5.4 percent (1.7 percent) to 4.4 percent (0.7 percent). The decline in returns is larger for sell than for buy quartiles, and all average excess returns remain positive (except exit when $k = 0$). Entry-to-exit returns also decline and remain statistically indistinguishable from zero. In sum, our results are not dramatically affected by the choice of return benchmarks. Results are available upon request.

V. Conclusions

We investigate the trading behavior of institutional investors from the third quarter of 1987 through the third quarter of 1995. We employ quarterly portfolio holdings of 1,200 institutions in approximately 5,000 firms over the sample period. These data represent about 6.7 million portfolio positions and an equity market value of $1.8 trillion toward the end of the sample period. Our analysis takes two forms. First, we decompose trading activity within institutional portfolios into the initiation of new equity positions (entry), the termination of previous equity positions (exit), and other adjustments to existing holdings. Second, we examine trading practices by different types of institutions and by institutions with different investment strategies.

We find that institutions act as momentum traders when they enter stocks but they act as contrarian traders both when they exit and when they make adjustments to ongoing holdings. The dollar value of an institution's portfolio devoted to entry or exit is positively related to lagged returns, and entry/exit typically takes place in small firms, consistent with Hong and Stein (1999). We find no evidence of institutional prescience—after a simple market adjustment and with no transaction costs, average entry-to-exit returns are close to zero. This appears to reflect a diversity in trading practices. Such diversity is also evident across different types of institutions. The sensitivity of changes in holdings to past returns is significantly higher for investment advisors and mutual funds than for pension funds and banks. Institutions that claim to follow growth and growth-and-value strategies are momentum traders, whereas institutions following value strategies are contrarian. Because of the large cross-sectional variation in institutional trading behavior, institutional trading is not, in the aggregate, destabilizing to stock prices.

With a large fraction of aggregate wealth under their management, institutions are frequently the marginal price-setting agents in securities markets. Therefore, an understanding of their trading behavior is an important prerequisite to an understanding of the dynamics of stock prices. Our characterization of institutional trading practices is designed to provide such an understanding. The large variation in trading practices among different types of institutions suggests that focusing on particular subsets of institutions provides a less than complete picture of trading behavior. The observation that mutual funds engage in momentum trading is not sufficient to conclude that their trading destabilizes asset prices because there are other types of institutions that follow offsetting strategies. This suggests that models in which multiple agents interact with each other may have an advantage over single-agent models in which all investors suffer from the same cognitive bias (Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998)).

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