Reconcilable Differences: Momentum Trading by Institutions

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Abstract

A number of recent studies test whether institutional investors, as a group, engage in momentum trading. Given directly observable returns and changes in institutional ownership, it is surprising that these studies reach vastly different conclusions. I re-examine the relation between changes in ownership structure and lag returns and, contrary to most recent studies, find strong evidence of institutional momentum trading. Moreover, I demonstrate that differences from previous studies arise from a number of factors including: (1) value-weighting versus equal-weighting across securities, (2) averaging versus aggregating over managers, (3) disagreement in the signs of measures of institutional demand (e.g., an institution buying a security while decreasing the security's portfolio weight), and (4) correlation between current capitalization and both lag returns and the absolute value of measures of institutional demand. Once controlling for these factors, the results across different methods are remarkably uniform – institutional demand is strongly related to cross-sectional variation in lag returns.

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I. Introduction

A number of studies suggest that institutional investors may momentum trade for a number of reasons including: overreaction to information, underreaction to information, agency problems, attraction to larger capitalization securities, the use of stop-loss orders, individual investors' reluctance to realize losses, and individual investors rebalancing their portfolios.[1] Moreover, given institutional investors account for 50 percent of stock ownership and 70 percent of trading volume (Schwartz and Shapiro, 1992), it is likely that institutions play a large role in setting equilibrium prices. If lag returns influence institutions' buy and sell decisions, and if such trading influences prices, then institutions' momentum trading patterns will have asset pricing implications. Specifically, such patterns may contribute to momentum and reversal patterns in stock returns, reflect the process by which information is incorporated into security prices, or result in excess volatility and destabilize asset prices.

Given its importance, it is not surprising that a number of previous studies investigate momentum trading by institutions. Table 1 summarizes 11 recent studies that focus on institutional momentum trading.[2] Unfortunately, the results across previous studies are widely discrepant – four of the 11 papers conclude that institutions do not momentum trade, five find relatively weak evidence of institutional momentum trading, and two find strong evidence of institutional momentum trading.[3] Thus, as a whole, extant evidence of

[1] See De Long, Shleifer, Summers, and Waldmann (1990a) and Daniel, Hirshleifer, and Subrahmanyam (1998) for models of momentum trading based on overreaction. See Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999) for models of momentum trading based on undereaction. Lakonishok, Shleifer, and Vishny (1992) argue that agency problems in the money management industry may cause institutional momentum trading. Badrinath, Gay, and Kale (1989), Del Guercio (1996), Falkenstein (1996), Gompers and Metrick (2001) and Bennett, Sias, and Starks (2003) demonstrate that institutional investors avoid small capitalization securities. Such behavior may lead to momentum trading, e.g., institutional investors selling stocks with large negative returns because such stocks are now "too small." De Long, Shleifer, Summers, and Waldman, (1990b) also point out that the use of stop-loss orders will induce momentum trading. Institutional momentum trading may also arise because other investors contrarian trade and institutions provide these investors the necessary liquidity (see, for example, Barber, Odean, and Zhu (2003)).

[2] The current study, as well as those listed in Table 1, focuses on cross-sectional momentum trading (i.e., comparing the lag return characteristics of stocks purchased by institutions at a point in time with those sold by institutions at the same point in time). A related literature focuses on time-series momentum trading by examining net investor flows following market increases or declines (e.g., Edelen and Warner, 2001). Although, Cai and Zheng (2004) examine both time-series momentum trading and cross-sectional momentum trading, this study discusses only their cross-sectional results.

[3] I classify Cai and Zheng's (2004) evidence as weak because their results indicate momentum trading is primarily limited to the purchase of past winners. For example, over months -2 to -12, securities in the fifth institutional demand decile underperformed the decile of securities most heavily sold by institutions (Table 4). I classify Nofsinger and Sias (1999) as weak because evidence of institutional momentum trading is limited to only half the capitalization deciles (Table VI,

institutional momentum trading is, at best, very weak. For example, Badrinath and Wahal (2002) (the most comprehensive previous study of institutional momentum trading) conclude that momentum trading by some institutions is offset by other institutions' contrarian trading, and therefore institutions, *as a group*, do not engage in momentum trading. As a result, the authors conclude that there is no evidence that institutional trading patterns are potentially "destabilizing."

[Insert Table 1 about here]

Given returns and changes in ownership structure are directly observable, it surprising that empirical results and conclusions differ so directly and so substantially. Taken as a whole, extant literature fails to tell us whether institutions, as a group, momentum trade. Thus, the goals of this study are to: (1) determine if institutions, as a group, momentum trade; and (2) reconcile results of the current study with the results of previous studies. To preview, my analysis reveals that, contrary to most recent studies, institutions strongly engage in momentum trading. Moreover, in reconciling my results with previous studies, I demonstrate that tests of momentum trading are complicated by a number of factors. First, some measures of institutional momentum trading are, for all practical purposes, measures of institutional momentum trading in the very largest of stocks. Second, some tests focus on average institutional demand while others focus on aggregate institutional demand. Third, there are often disagreements in the signs of the measures of institutional demand. For example, an institution may buy additional shares of a security but decrease the security's portfolio weight (if the institution purchases other securities to a greater extent). Fourth, the lack of independence between current capitalization, lag returns, and the *absolute value* of measures of institutional demand complicates tests of momentum trading. For example, the absolute value of changes in the fraction of outstanding shares held by institutions is positively correlated with current capitalization, e.g., it is more common for a large security to move from 75 percent to 65 percent institutional ownership than for a small security to move from 15 percent to 5 percent institutional ownership. In addition, current capitalization is

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Panel A). I classify Wermers (1999) as weak because evidence is primarily limited to the two smallest capitalization quintiles (Table VIII). I classify Grinblatt, Titman and Wermers (1995) as weak because their evidence is limited to the purchase of large capitalization lag winners. I classify Lakonishok, Shleifer, and Vishny (1992) as weak because their evidence is limited to the sale of small capitalization lag losers.

strongly correlated with lag returns, e.g., if two securities were the same size a year ago, the one that garnered a large negative return over the past year will now be much smaller than the one that garnered a large positive return over the past year. Thus, if one sorts securities into quintiles by changes in the fraction of shares held by institutions, large capitalization securities (that average larger *lag* returns than small capitalization securities) will play a more important role in both the extreme institutional buy portfolio and the extreme institutional sell portfolio. Analogously, small capitalization securities (that average smaller *lag* returns) will play a more important role in the less extreme portfolios. Once controlling for these four factors, the results across different methods are remarkably uniform – institutional demand is strongly related to cross-sectional variation in lag returns.

The balance of the paper is organized as follows. I review the data in the next section. In Section III, I present the basic empirical tests of institutional momentum trading. I reconcile my results with previous tests of momentum trading and discuss the strengths and weaknesses of different approaches in Section IV. The final section contains a summary and suggestions for future work.

II. Data

This study uses quarterly institutional ownership data (from CDA-Spectrum/Thompson Financial) derived from institutional investors' 13F reports to examine institutional trading.[4] The data cover the first quarter of 1983 through the fourth quarter of 2003, for a total of 84 quarters. I require the manager file both beginning- and end-of-quarter reports to be included in the sample. Historical cusips, shares outstanding, returns, capitalizations, and share adjustment factors are taken from the Center for Research in Security Prices (CRSP) for domestic ordinary shares listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and NASDAQ.[5] Each quarter, I compute the total number of managers reporting

[4] All professional investors with at least $100 million in equity securities under management are required to file reports of their positions in each security within 45 days of the quarter-end. Institutions are required to report all equity positions greater than either 10,000 shares or $200,000 in market value. Typically, 13F reporting is aggregated across different units within an institution, e.g., Fidelity Management and Research files one report that covers all Fidelity positions.

[5] I include all securities with a CRSP share code of 10 or 11 and require securities to have the same beginning and end of quarter CUSIP number. I use CRSP's share adjustment factor to account for changes in holdings due to stock splits and stock dividends and exclude securities whenever the reported fraction of shares held by institutions exceeds 100 percent.

their holdings, as well as the cross-sectional averages of the number of securities in their portfolio, and the value of their equity holdings. Panel A in Table 2 reports the time-series average (and other descriptive statistics) of these quarterly cross-sectional means.

[Insert Table 2 about here]

On average, the sample consists of 1,098 managers each quarter (ranging from 552 in the fourth quarter of 1983 to 1,828 in the third quarter of 2003). These managers hold, on average, 250 securities in a portfolio worth $2.5 billion. In total, the data cover over 23 million quarterly institutional investor positions.

Panel B in Table 2 reports the time-series average of the cross-sectional mean number of securities in the sample and fraction of shares held by institutional investors. On average, the sample contains 5,229 securities, averaging 26 percent of their shares held by institutions. I also compute the averages by capitalization quintile (capitalization quintiles, based on the sample of securities included in the analysis, are formed at the beginning of each quarter).[6] The results reveal a monotonic positive relation between the fraction of shares held by institutions and capitalization.

Panel C reports the time-series means of the cross-sectional average market-adjusted (CRSP value-weighted index) returns for securities within each capitalization quintile over the previous quarter, six months, and year. The results reveal a strong positive relation between current capitalization and lag return. For example, the time-series average of the cross-sectional mean market-adjusted return over the previous year for stocks in the bottom capitalization quintile is –20.15 percent versus 13.41 percent for stocks in the top capitalization quintile.

I compute aggregate institutional demand for security *i* in quarter *t* as the change in the number of shares held by institutional investors divided by the number of shares outstanding for security *i*, i.e., the fraction of outstanding shares moving to institutional investors from other investors:

(1) $$\Delta\%Shares_{i,t} = (\#Shares\ Held\ by\ Institutions_{i,t} - \#Shares\ Held\ by\ Instituions_{i,t\text{-}1})/(\#Shares\ Outstanding_{i,t})$$

$$= (\#Shares\ Purchased\ by\ Institutions_{i,t} - \#Shares\ Sold\ by\ Institutions_{i,t})/(\#Shares\ Outstanding_{i,t}).$$

[6] Although institutions favor larger capitalization securities, few securities have no institutional ownership. As a result, the sample includes nearly all ordinary shares.

III. Do Institutions Momentum Trade?

I begin by comparing the lag return characteristics of securities sorted by institutional demand. Because both the *absolute value* of changes in the fraction of shares held by institutions and lag returns are positively correlated with capitalization, I compute capitalization-stratified change in fractional ownership quintiles. Specifically, at the beginning of each quarter securities are partitioned into capitalization quintiles. Within each capitalization quintile, securities that experience an increase in institutional ownership are partitioned into large and small increase groups by sorting into two equal-size portfolios. Similarly, within each capitalization quintile, securities that experience a decrease in institutional ownership are partitioned into large and small decrease groups by sorting into two equal-size portfolios. Securities that experience no change in institutional ownership form the final group.

Securities are then re-aggregated over capitalizations, each quarter, by the change in fractional ownership ranking, resulting in five capitalization-stratified change in fractional ownership portfolios. I then compute the cross-sectional average market-adjusted (CRSP value-weighted index) return over the contemporaneous quarter, the lag quarter, the lag six months, and the lag year, for securities within each portfolio. Because institutional ownership increases over the sample period (Gompers and Metrick, 2001), the average number of securities in the increase portfolios is greater than the average number of securities in the decrease portfolios. In addition, few securities experience no change in institutional ownership within a given quarter. Small firms, with low levels of institutional ownership, however, are more likely to experience no change in institutional ownership than large firms. Thus, although the four increase and decrease groups are capitalization-stratified, small firms dominate the no-change group.

Panel A in Table 3 reports the time-series average of the 83 cross-sectional mean market-adjusted returns for securities in each capitalization-stratified change in fractional ownership portfolio. The second to last row in Panel A reports the results of an *F*-test of the null hypothesis that returns do not differ over the five portfolios. Because the "no change" portfolio is dominated by small stocks (and therefore, not capitalization-stratified), I also compute an *F*-test (reported in the last row of Panel A) of the null hypothesis that returns do not differ across quintiles one, two, four, and five, i.e., excluding the no-change portfolio. These *F*-statistics are calculated from the time-series of the 83 cross-sectional means for each change in ownership quintile.[7] The first and second columns in Table 3 report the time-series means of the cross-sectional average change in the fraction of shares held by institutional investors and number of securities within each portfolio, respectively.

[Insert Table 3 about here]

The results in Panel A reveal that, in aggregate, institutions momentum trade. Securities most heavily sold by institutional investors, averaging 4.04 percent of their shares moving from institutions to other investors, average market-adjusted returns of -3.59 percent in the prior quarter, while those most heavily purchased by institutions, averaging 4.34 percent of their shares moving from other investors to institutions, average market-adjusted returns of 4.92 percent in the prior quarter. The same pattern is documented for contemporaneous quarter returns, lag six month returns, and lag annual returns. Differences in lag (or contemporaneous) returns are statistically significant at the 1 percent level in every case.[8]

IV. Reconciliation with Previous Work

A. Momentum Trading and Firm Size

As noted in the introduction, differences in results across previous studies are related to capitalization for two reasons: (1) some measures of momentum trading are, essentially, value-weighted measures, and (2) current capitalization is correlated with both lag returns and the absolute value of some measures of institutional demand.[9] Thus, to understand why different tests of momentum trading yield different results, one must understand how momentum trading differs across capitalizations. Therefore, I begin to reconcile the strong evidence of momentum trading presented in Panel A of Table 3 with the generally weak evidence

[7] Although not reported (to conserve space), I also compute non-parametric Kruskal-Wallis (analogous to a Wilcoxon rank-sum test for more than two categories) statistics instead of *F*-statistics. All the rank-sum statistics are significant at the 1 percent level.

[8] Because the no-change portfolio is primarily composed of small securities (and therefore not directly comparable to the other capitalization-stratified portfolios), average lag market-adjusted returns are uniformly negative for the no-change portfolio (see Panel C of Table 2).

[9] As pointed out by Badrinath and Wahal (2002), it is also possible that differences in results may be driven by differences in samples. For example, as shown in Table 1, some previous studies focus on subsets of institutions such as mutual funds. Nonetheless, the results in this section demonstrate that differences in methods primarily explain the differences in results.

found in most previous studies (see Table 1) by investigating the relation between institutional momentum trading and firm size. Specifically, I use two sorting techniques to evaluate the relations between firm size, lag return, and changes in ownership. First, analogous to Panel A of Table 3, I examine contemporaneous and lag return differences of portfolios sorted on changes in ownership within each capitalization quintile. The strength of such an approach is that one can directly compare the characteristics of those securities that experienced the most extreme changes in ownership holding capitalization constant and evaluate returns of any lag for a given portfolio.[10] For example, although large stocks average higher *lag* returns than small stocks, one can test whether the large stocks most heavily sold by institutions previously underperformed the large stocks most heavily purchased by institutions. The weakness of such an approach is that comparisons across capitalization quintiles are clouded because average *lag* returns differ systematically across capitalizations.[11]

Second, I examine changes in ownership for securities sorted independently on lag return and capitalization. The strength of this approach is that one can compare the relative propensity of institutions to momentum trade across capitalization quintiles. The limitation of this approach is that one cannot evaluate, for example, the lag return characteristics of most large stocks institutions are selling (or small capitalization stocks institutions are buying) because large stocks are disproportionably lag winners (and small stocks are disproportionably lag losers). In addition, this approach limits the evaluation of changes in ownership to a specific lag return, i.e., instead of evaluating the lag return characteristics of stocks most heavily sold by institutions, I evaluate the change in ownership for stocks sorted by a specific lag return (e.g., lag six month returns).

I begin by examining average returns for securities within each capitalization quintile (based on beginning of quarter t capitalization) sorted by the change in the fraction of shares held by institutional investors.

[10] Because the absolute value of changes in institutional ownership is positively correlated with capitalization, sorting on changes in the fraction of shares held by institutions within each capitalization quintile may not fully control for capitalization. Unreported empirical tests reveal, however, that differences in capitalization across institutional demand quintiles within each capitalization quintile are relatively small.

[11] Thus, for example, although large stocks most heavily purchased by institutional investors (e.g., the 20 percent of large stocks most heavily purchased by institutions) will contain many extreme winners, the large stocks most heavily sold by institutions (e.g., the 20 percent of large stocks most heavily sold by institutions) will contain few extreme losers. This limitation does not affect the analysis of contemporaneous quarter returns.

Specifically, I disaggregate the results in Panel A of Table 3 and report results by capitalization quintile in Panels B through F of Table 3. If, within a given capitalization quintile, the no-change category averages less than 50 observations each quarter, I exclude the category.[12] The last row in each panel presents *F*-statistics associated with the null hypothesis that the time-series of the cross-sectional mean returns do not differ across the reported change in ownership quintiles.

The results reported in Table 3 reveal that institutions momentum trade in stocks of all capitalizations. For example, the difference in contemporaneous quarter returns of securities most heavily purchased by institutions and those most heavily sold by institutions are large and positive for every capitalization quintile (although somewhat stronger for middle- and large-capitalization securities), consistent with intra-quarter momentum trading by institutions.[13] Similarly, institutions momentum trade in every capitalization quintile at a one-quarter lag. For the smallest 80 percent of stocks, the average return differences between the top and bottom change in ownership quintiles within each size quintile are similar (7 to 11 percent). The lag one-quarter return difference is smaller in the top capitalization quintile, averaging 3 percent. The results for lag six-month returns for all capitalizations and the results for lag one year returns for the smallest 80 percent of stocks exhibit similar patterns. For the largest capitalization quintile, however, I find some evidence that the stocks institutions most heavily purchased slightly underperformed the stocks institutions most heavily sold over the previous year. In general, the difference in lag returns between stocks most heavily purchased by institutions and those most heavily sold by institutions are weakest for the largest capitalization portfolios.

Next, I examine changes in ownership for securities sorted independently by capitalization (at the beginning of quarter *t*) and return over the same quarter, the lag quarter, the lag six months, or the lag year. Results for sorts based on the contemporaneous quarter return (Panel A), the lag quarter return (Panel B), the lag six months return (Panel C), and the lag annual return (Panel D) are reported in Table 4. Columns

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[12] The results in Table 2 show that *lag* returns are positively correlated with current capitalization, i.e., stocks that performed poorly over the past year are more likely to be (correctly) classified as currently small. In addition, one cannot sort on size prior to the examination of lag returns (e.g., sort on size at the beginning of quarter *t*-4), because such a research design fails to control for size at the time of the change in institutional ownership.

[13] The contemporaneous quarterly relation is also consistent with the hypothesis that aggregate institutional trading impacts security prices (see, for example, Gibson and Safieddine, 2002).

represent the performance sorts, while rows represent the capitalization sorts. The first five rows in each panel report the time-series average of the cross-sectional mean market-adjusted return over the indicated period for securities in each capitalization/lag performance group, as well as the fraction of observations accounted for by securities in that capitalization/lag performance group (in parentheses). As shown in the first cell of Panel A, for example, small capitalization losers accounted for 5.43 percent of the observations in the contemporaneous quarter sorts and averaged a market-adjusted contemporaneous quarter return of -33.60 percent.

[Insert Table 4 about here]

The next five rows in each panel report the time-series average of the cross-sectional mean adjusted change in the fraction of shares held by institutions. I define the adjusted change in the fraction of shares held by institutions for security *i* (in size quintile *q*) in quarter *t* as the raw change that quarter less the mean change that quarter for securities within the same capitalization quintile divided by the cross-sectional mean fraction of shares held by institutions that quarter for securities within the same capitalization quintile:

$$\text{(2)} \qquad Adjusted\ \%\Delta_{i,t} = \frac{\Delta\%Shares_{i,t} - \overline{\Delta\%Shares}_{i\in q,t}}{\overline{\%Shares}_{i\in q,t}}.$$

This approach accounts for the systematic increase in institutional ownership over the sample period and, because institutional ownership *levels* differ across capitalization (see Table 2), allows comparisons across capitalizations. Thus, the adjusted change in ownership measures the abnormal change (i.e., accounting for the average growth in institutional ownership) in the fraction of shares held by institutions normalized by the average fraction of shares held by institutions in similar-sized securities.[14] In addition, the last column reports an *F*-statistic based on the time-series of the cross-sectional mean adjusted change in fractional ownership, testing the null hypothesis of equality across the lag (or contemporaneous quarter) return quintiles within each capitalization quintile.[15]

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[14] I divide by the average institutional ownership across securities in the same capitalization quintile (at time *t*) rather than the firm's institutional ownership because some firms (especially small firms) have very low levels of initial institutional ownership, and in some cases, no initial institutional ownership. This leads to very high (or undefined) percentage changes in institutional ownership at the security level.

[15] Non-parametric tests yield qualitatively identical results.

The results in Table 4 reveal that institutions momentum trade in securities of every capitalization and at every lag evaluated. Specifically, the adjusted change in institutional ownership for winners is greater than the adjusted change in institutional ownership for losers in every case. Further consistent with Table 3, the results in Table 4 suggest that institutional momentum trading is weakest in the largest capitalization securities, especially at longer lags. For example, based on lag six-month returns (Panel C), the difference between winners' and losers' adjusted change in fractional ownership is 8.11 percent for stocks in the smallest capitalization quintile, 8.95 percent for stocks in the middle capitalization quintile, and 1.83 percent for stocks in the largest capitalization quintile.

Inconsistent with Table 3, however, the results in Panel D reveal that aggregate changes in institutional ownership are positively related to lag *annual* returns for large capitalization securities.[16] The results in the first five rows of Panel D help explain why Tables 3 and 4 differ with respect to lag annual returns in large capitalization securities. While Table 3 examines the lag return characteristics of the quintile of large stocks most heavily sold by institutions, Table 4 reveals that only 1.13 percent of securities are in the bottom performance quintile and top capitalization quintile. Given five capitalization groups and five contemporaneous or lag return groups, each cell would account for approximately 4 percent of the total observations, if lag return and size were independent.[17] The positive correlation between current size and lag return means that very few large capitalization securities are extreme lag annual losers. Specifically, as shown in Panel D, over 40 percent (0.0802/0.20) of the worse lag annual performance quintile securities are in the smallest capitalization quintile and less than 6 percent (0.0113/0.20) are in the top capitalization quintile.[18] In sum, although the results in Tables 3 and 4 reveal institutional investors momentum trade in stocks of all

[16] The adjusted change in ownership for large stocks is not monotonic across lag annual return quintiles. Specifically, evidence of institutional momentum selling is much greater than evidence of institutional momentum buying in large stocks.

[17] Not surprisingly, the results in Table 4 reveal that although few small securities are in the extreme lag winner quintile, even fewer large securities are in the extreme lag loser quintile. That is, it is more likely a very small security that doubles in size remains classified as small than a large security that loses half its value remains classified as large.

[18] The results in Table 4 also suggest why, when ignoring the relation between lag return and current capitalization, evidence of institutional "buy" momentum trading is typically stronger in large capitalization securities (e.g., the implicit value-weighting in Grinblatt, Titman, and Wermers, 1995) and evidence of institutional "sell" momentum trading is typically stronger in small capitalization securities (e.g., equal-weighting in Chen, Hong, and Stein, 2002). The positive correlation between lag return and current capitalization means that large stocks contain a disproportionate number of lag winners and small stocks contain a disproportionate number of lag losers.

capitalizations, the results also reveal that institutional momentum trading is weakest (especially at longer lags) in the very largest of stocks. Moreover, the weaker relation between institutional demand and lag returns for large stocks is driven, at least in part, from the fact that few extreme lag losers remain large stocks.

B. Lag Returns and Changes in Portfolio Weights

Grinblatt, Titman, and Wermers (1995) measure momentum trading for each institution *j* in quarter *t* as the sum of the products of the quarterly change in the institution's portfolio weight in the stock and the stock's lag (or contemporaneous quarter) market-adjusted return:[19]

(3) $$GTW_{j,t}(k) = \sum_{i=1}^{N} (w_{i,j,t} - w_{i,j,t-1})(R_{i,t-k} - R_{m,t-k}),$$

where $w_{i,j,t}$ ($w_{i,j,t-1}$) is institution *j*'s security *i* portfolio weight at the end (beginning) of quarter *t* and $R_{i,t-k}$ is the return for security *i* over the same quarter (k=0), the previous quarter (k=1), the previous six months (k=2 quarters), or the previous year (k=4 quarters). Similarly, $R_{m,t-k}$ measures the return on the CRSP value-weighted index over the same *k* period.[20] Because the measure is the product of lag returns and the difference between end-of-quarter and beginning-of-quarter portfolio weights, the *GTW* measure has a straightforward interpretation – $GTW_{j,t}(k)$ is the difference in the lag *k* quarter returns of the portfolio institution *j* held at the end of quarter *t* and the portfolio institution *j* held at the beginning of quarter *t*.

Based on a sample of mutual funds, Grinblatt, Titman, and Wermers (1995) report that, on average, the portfolio held by a fund at the end of a given quarter had outperformed the portfolio held by the fund at the beginning of the quarter by only 30 basis points over the previous quarter. Badrinath and Wahal (2002) examine the *GTW* measure for a sample similar to mine (i.e., 13F data) from 1987-1995 and find even weaker

[19] Because the portfolio weights for each institution sum to one at both time *t* and *t*-l, subtracting the market return does not affect the measure when the sample includes all securities in the manager's portfolio. When limiting the sample to a subset of the manager's trades, however, subtracting the market return will affect the estimate. For example, Grinblatt, Titman, and Wermers (1995) separately analyze past winners and past losers.

[20] As pointed out by Grinblatt, Titman, and Wermers (1995), stocks that increase in value over a quarter will tend to have larger portfolio weights at the end of the quarter than the beginning even if the institution does not trade the security. To eliminate such "passive momentum," I follow Badrinath and Wahal (2002) and compute beginning- and end-of-quarter portfolio weights with end-of-quarter prices.

evidence of institutional momentum trading. For example, the lag quarterly *GTW* measure (i.e., k=1) for Badrinath and Wahal's sample averages only five basis points.

I find similar results for my sample. Following and Badrinath and Wahal (2002), I compute the pooled cross-sectional time-series average *GTW* measure for the 91,132 institution-quarter observations in my data.[21] The results reveal only weak evidence of short-term institutional momentum trading and essentially no evidence of institutional momentum trading over longer lags. Specifically, the *GTW* measure based on same quarter returns averages 22.9 basis points (statistically significant at the 1 percent level).[22] At a one-quarter, six-month, and one-year lag, the pooled *GTW* measure averages -3.2, -8.0, and -26.3 basis points.[23] Thus, for my sample, the average institutional investor's portfolio at the end of quarter t had essentially the same quarter t-1 performance as the portfolio the institution held at the beginning of quarter t. In short, consistent with Grinblatt, Titman, and Wermers (1995) and Badrinath and Wahal (2002), the *GTW* metric suggests that, on average, institutions do not momentum trade.

I begin to resolve the differences between the results in the previous section and the *GTW* metric by hypothesizing that *GTW* will primarily measure momentum trading in large capitalization securities because: (1) *GTW* is measured at the institution, rather than the security, level; (2) institutions favor large capitalization securities; and (3) the absolute value of changes in portfolio weights (i.e., the first portion of the *GTW* metric) will tend to be greater for large capitalization stocks because large stocks account for most of the market's portfolio weight (by definition).

To evaluate the relations between the *GTW* metric and firm size, I disaggregate *GTW* at the institution level and examine each institution-security-quarter observation's contribution to the *GTW* metric (henceforth, the "*GTW* contribution"), i.e., the product of the change in the institution's portfolio weight for that security and the lag (or contemporaneous quarter) market-adjusted return for that security. Columns three through

[21] Because the number of institutions grows over time, this pooling weights more recent data greater than more distant data. The time-series average of the quarterly means, however, are similar. In contrast, Grinblatt, Titman and Wermers (1995) report the average across mutual funds that survive the 10 year sample period.
[22] I compute t-statistics from time-series standard errors of the 83 quarterly cross-sectional means (following Badrinath and Wahal, 2002).
[23] The average *GTW* measure based on lag one quarter returns or lag six month returns do not differ significantly from zero at traditional levels. The lag one year measure differs significantly from zero at the 5 percent level.

six of Panel A in Table 5 report the pooled cross-sectional time-series mean *GTW* contribution for the approximately 23.1 million institution-security-quarter positions in my data (reported figures are in percent of basis points). The *t*-statistics (reported in parentheses) are based on the time-series of the 83 cross-sectional means. The results are consistent with previous studies and the average *GTW* results discussed above. Although the average *GTW* contribution is positive and statistically significant (at the 1 percent level) for the contemporaneous quarter, the average contribution does not differ significantly from zero for the lag quarter or the lag six months, and is negative (and statistically significant at the 5 percent level) when computed from lag annual returns.

[Insert Table 5 about here]

To evaluate the role of large stocks in computing the average *GTW*, I partition the 23.1 million manager-security-quarter contributions reported in Panel A by capitalization quintile. In addition, I compute the pooled cross-sectional time-series average (across manager-security-quarter observation) absolute portfolio weight change by capitalization quintile. The results reported in the first column of Panels A and B reveal that 50 percent of the sample observations arise from securities in the largest capitalization quintile (11,508,985/23,145,675). In addition, consistent with the hypothesis that the *GTW* metric primarily measures momentum trading in large capitalization securities, the results reported in the second column reveal a monotonic positive relation between the absolute portfolio weight change and firm size. The average absolute portfolio weight change in large capitalization stocks is nearly eight times greater than that for stocks in the smallest capitalization quintile (0.158/0.020). Thus, for example, if a small stock beats the market by 5 percent over the previous quarter and institutions double their average portfolio weight change, the contribution to the *GTW* measure is 0.0020 basis points (0.020 percent*2*0.05). Alternatively, for a large stock and the same conditions, the contribution to the *GTW* measure is over eight times larger (0.0158 basis points). In sum, the analysis presented in the first two columns of Panel B reveals that the average *GTW* metric is largely a measure of institutional momentum trading in large capitalization securities.

The last four columns in Panel B report the mean contributions to the *GTW* metric by capitalization quintile and the associated *t*-statistic (computed from the time-series of the 83 cross-sectional means). Note that the averages reported in Panel A can be derived from calculating the weighted (by number of observations) average *GTW* across the capitalization quintiles in Panel B.[24] The results reported in Panel B are largely consistent with those reported in the previous sections (e.g., Table 3) – evidence of institutional momentum trading in all but the very largest of securities.

Another potential reason for differences between the results in the current study and the *GTW* metric is that the same trade may be classified as a "buy" by one measure and a "sell" by the other. Specifically, it is possible for an institution to purchase (sell) a stock, while at the same time decreasing (increasing) the stock's portfolio weight. For instance, if an institution receives a net inflow of $2 and invests $1 in the existing portfolio and $1 in a new security, the portfolio weights for all the positions held at the beginning of the quarter will decline. For all practical purposes, the trading of *any* security in a portfolio will change portfolio weights for *all* securities held in the portfolio – including those securities not traded.

Of the 23,145,675 institution-security-quarter positions in my dataset (Panel A), the sign of the institution's portfolio weight change is inconsistent with the sign of the institution's trading in 29 percent of the observations. Panels C and D in Table 5 reports statistics analogous to those reported in Panels A and B, respectively, when excluding these 29 percent of observations. The results reveal that these observations also help explain differences between my analyses and the *GTW* metric – the point estimates and *t*-statistics for every lag in the four smallest capitalization quintiles are greater in Panel D than Panel B. The results in Panel D are fully consistent with those reported in the previous sections (e.g., Table 3) – strong evidence of institutional momentum trading in all but the very largest of securities.

The last major difference between the *GTW* metric and the results reported in the previous section is that the *GTW* metric measures momentum trading at the institution level (i.e., does an institution momentum trade?) whereas my tests focus on momentum trading at the security level (i.e., do institutions momentum

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[24] This holds exactly for the *GTW* contribution measured over the current and previous quarters. Because I do not require securities to have lag six month or annual data to be included in the sample, the number of observations (and therefore weights) are slightly different for lag six-month or lag annual returns.

trade in a security?). Thus, differences between my results and the *GTW* analysis may arise, at least in part, because institutions act differently on average than in aggregate (e.g., large institutions momentum trade but small institutions contrarian trade). Moreover, not all managers are likely to have the same impact on the average *GTW* metric. Specifically, smaller institutions will likely have a disproportionately large impact on the average *GTW* measure because smaller institutions have fewer positions and, as a result, larger portfolio weights and larger changes in portfolio weights. Consistent with this hypothesis, the time-series mean of the cross-sectional correlation between the average absolute value of the manager's change in portfolio weight and the value of the manager's portfolio averages -6.9 percent (statistically significant at the 1 percent level).[25]

To evaluate institutional investors' aggregate, rather than average (across managers), effect, I compute an *aggregate GTW* measure each quarter as the sum (across securities) of the products of *aggregate* institutional portfolio weight changes and lag (or contemporaneous quarter) returns. The time-series of the aggregate quarterly *GTW* measures (reported in Panel E) for the contemporaneous quarter, the lag quarter, the lag six months, and the lag year, averages 21.7 basis points, 7.5 basis points, 11.2 basis points, and 8.9 basis points, respectively. Thus, unlike the average (across managers) *GTW*, the aggregate *GTW* metric is positive, albeit small, at all lags (and statistically significant at the 1 percent level for the contemporaneous quarter, the lag quarter, and the lag six months), indicating momentum trading by institutions in aggregate.[26]

In addition, to examine aggregate (rather than average) institutional momentum trading by capitalization, I compute the contribution to the aggregate *GTW* by capitalization quintile, i.e., the sum of the products of aggregate changes in institutional portfolio weights and lag returns for securities within each capitalization quintile. The results, reported in Panel F, are fully consistent with those reported in Table 3 – there is strong evidence of institutional momentum trading in the smallest 80 percent of securities. (Note that summing over capitalization quintiles in Panel F yields the aggregate *GTW* reported in Panel E.)[27]

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[25] Each quarter, I compute each manager's portfolio weight change in each security. I then average the absolute value of these portfolio weight changes for each manager (each quarter) and compute the cross-sectional correlation between the average absolute portfolio weight change and the total value of the manager's portfolio. Last, I compute the time-series average of the 83 cross-sectional correlations. The statistical significance is determined by standard error of the time-series of 83 cross-sectional correlations.

[26] Statistical significance determined by the time-series of the quarterly aggregate measure.

[27] Because, as discussed above, changes in portfolio weights are larger for large capitalization stocks, the aggregate *GTW* metric also tends to be larger for large capitalization stocks.

C. The Holdings Ratio Metric

Badrinath and Wahal (2002) also examine momentum trading by evaluating lag returns of stocks sorted on the number of shares of stock *i* held by institution *j* at the end of quarter *t* divided by the number of shares held by the institution at the end of quarter *t*-1 (denoted *Hratio*):

(4) $$Hratio_{i,j,t} = H_{i,j,t}/H_{i,j,t\text{-}1}.$$

The authors sort institution-security-quarter observations into nine groups: Entry ($H_{i,j,t}> 0$, $H_{i,j,t-1}=0$), high-buy ($Hratio_{i,j,t}>1.3$), medium-buy ($1.3\geq Hratio_{i,j,t}>1.1$), low-buy ($1.1\geq Hratio_{i,j,t}>1$), no change ($Hratio_{i,j,t}=1$), low-sell ($1>Hratio_{i,j,t}\geq 0.9$), medium-sell ($0.9>Hratio_{i,j,t}\geq 0.7$), high-sell ($0.7>Hratio_{i,j,t}$), and exit ($H_{i,j,t}=0$, $H_{i,j,t-1}>0$). Average market-adjusted returns are then computed for observations within each group, pooled over institutions, securities, and quarters, and compared across groups. Badrinath and Wahal (2002) posit that if institutional investors tend to buy (sell) most intently those stocks that experienced high (low) lag returns, then average lag returns should decline as one moves from entry to exit.

Badrinath and Wahal (2002) report that average lag market-adjusted returns for all nine groups tend to be positive. Moreover, the average return is highest for those observations in the entry category. Thus, consistent with their analysis of the average *GTW* measure, the results suggest that institutions momentum trade on entry (i.e., stocks institutions purchased outperformed the market), but contrarian trade on exit (i.e., stocks institutions sold also outperformed the market) and, as a result, have little net effect.

Following Badrinath and Wahal (2002), Panel A of Table 6 reports the pooled cross-sectional time-series mean market-adjusted return for the approximately 23.1 million institution-security-quarter observations sorted into the nine *Hratio* categories discussed above. Further following Badrinath and Wahal, I compute *t*-statistics from paired *t*-tests based on the null hypothesis that the time-series of cross-sectional mean returns for the *Hratio* category does not differ from the no-change group (*Hratio*=1). Although I do not report the *t*-statistics (to conserve space), nearly all the results are statistically significant at the 5 percent level or better.[28] The results reveal some evidence of institutional momentum trading – stocks institutions buy tend to have

[28] Only two of 42 lag returns estimates (four buy categories plus four sell categories times three different lags) are not statistically significant at the 5 percent level (the exit previous quarter and previous six months categories).

outperformed the market in the same or previous quarters. Further consistent with Badrinath and Wahal, however, the *Hratio* analysis suggests institutional investors contrarian trade in their selling, e.g., average lag market-adjusted returns from sell and exit portfolios are also positive. Thus, consistent with Badrinath and Wahal, the results suggest that institutions momentum trade in their buying but contrarian trade in their selling and therefore, as a group, are neither momentum or contrarian traders.

[Insert Table 6 about here]

Similar to the *GTW* metric, I hypothesize that because institutional investors favor larger capitalization securities and *Hratio* is averaged over manager-security-quarter observations, *Hratio* will primarily focus on large capitalization securities. Consistent with this hypothesis, the average *Hratio* observation is from the 82nd capitalization percentile (capitalization percentiles are computed at the beginning of each quarter). Moreover, as noted previously, firm size is positively correlated with lag return. As a result, comparisons across *Hratio* categories will be clouded if the absolute value of *Hratio* is not independent of firm size across the categories.[29] To examine the relation between firm size and *Hratio*, I compute the average capitalization percentile for each institution-security-quarter observation within each of the nine *Hratio* categories. The results (reported in the second column of Panel A) reveal that small firms play a larger role in the entry, exit, and no change groups than the other categories. Because smaller firms average lower *lag* returns than larger firms (see Table 2), differences in firm size between *Hratio* categories help explain why the no change group exhibits the lowest average lag return at the six- and 12-month lag and why the exit group exhibits the lowest value at the one-quarter lag.

In addition, given small firms have greater return skewness (i.e., bound by –1 from below, but unbounded from above), average returns over categories that differ across firm size may be misleading. To examine the effect of differences in skewness across *Hratio* categories, I calculate the fraction of manager-security-quarter observations that exceed the market return over the lag return period. The last four columns in Panel A report the fraction of manager-security-quarter observations with positive market-adjusted returns

[29] The value-weighted *lag* market-adjusted return has an expected value greater than zero if weights are based on market capitalization at the beginning of quarter t=0. This pattern helps explain why average lag returns for all *Hratio* categories are greater than zero.

within each *Hratio* category. The results reveal that differences in return skewness (driven by differences in capitalization) across *Hratio* categories help explain some of the difference between *Hratio* and the results in the previous section. Specifically, the fraction of positive observations declines nearly monotonically as one moves from entry to exit, consistent with momentum trading.

Following Badrinath and Wahal (2002), I average *Hratio* observations over manager-security-quarters. Thus, similar to *GTW*, the results may not reflect aggregate institutional demand because observations are averaged, rather than aggregated, over managers. Unlike *GTW*, however, larger managers (who hold a greater number of securities) will play a larger role in computing the average *Hratio* pooled over manager-security-quarters. Consistent with this hypothesis, I find the average *Hratio* observation is from the 75th manager size percentile (manager size percentiles are computed at the beginning of each quarter based on the total dollar value of the manager's holdings). More important, the role of small and large managers may differ over *Hratio* categories. Specifically, I hypothesize small managers are more likely to completely exit a security, make no change in a position, or enter a new security. To examine this possibility, I compute the average manager percentile for observation within each of the nine *Hratio* categories. The results (reported in the third column of Panel A) reveal that small managers play a larger role in the entry, exit, and no change groups than the other categories.[30]

To examine aggregate, rather than average, institutional momentum trading, I compute an aggregate *Hratio* for each stock-quarter as the ratio of the number of shares of security *i* held by institutions in aggregate at the end of the quarter to the number of shares held in aggregate at the beginning of the quarter.[31] Because there is only one aggregate *Hratio* for each security, the cross-sectional average *Hratio* (at time *t*) is no longer dominated by large capitalization stocks. More extreme *Hratio*s, however, are more common in smaller capitalization securities (i.e., the absolute value of the aggregate *Hratio* is negatively correlated with capitalization). Therefore, to control for the correlation between absolute *Hratio*, firm size, and lag return,

[30] Although specific results are not reported (to conserve space), differences in capitalization percentiles and manager size percentiles across *Hratio* categories are statistically significant at the 1 percent level.
[31] If a security has zero initial aggregate institutional ownership, I set the aggregate *Hratio* arbitrarily large to ensure the firm is placed in the top *Hratio* quintile.

each quarter I sort securities into aggregate *Hratio* quintiles within each capitalization quintile.[32] Panel B in Table 6 reports the time-series of the cross-sectional average market-adjusted lag six-month return and fraction of securities that outperformed the market over the previous six months for securities within each capitalization and aggregate *Hratio* quintile. The results in Panel B reveal strong evidence of institutional momentum trading in all capitalization quintiles.[33] Moreover, the *F*-statistic reported in the last row in Panel B reveals that differences in mean returns or fraction of securities that outperform the market across aggregate *Hratio* categories are statistically significant (at the 1 percent level) for every capitalization quintile.[34]

D. Regression Tests

Several studies (e.g., Falkenstein, 1996; Gompers and Metrick, 2001) document a negative relation between the fraction of shares held by institutional investors and lag returns, once accounting for other security characteristics including share price and capitalization. Bennett, Sias, and Starks (2003) report, however, that *changes* in the fraction of shares held by institutional investors are positively related to lag returns, even when controlling for other security characteristics (including share price and firm size). As a result, Bennett, Sias, and Starks conclude that the combined evidence suggests institutional investors are momentum traders. In addition, Burch and Swaminathan (2001) report that, although current institutional ownership levels are negatively related to lag return, future institutional ownership levels are positively related to lag returns. In unreported analyses, I repeat the Bennett, Sias, and Starks tests of regressing both levels and changes in institutional ownership on their set of security characteristics (beta, total volatility, firm-specific volatility, firm size, firm age, dividend yield, share price, turnover, and lag return) and find that cross-

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[32] I sort into *Hratio* quintiles within each capitalization quintile (rather than forming fixed *Hratio* cutoffs as in Panel A) for two reasons. First, few firms have no institutional ownership. Thus, the number of observations in aggregate entry and exit categories is extremely small (or zero, in the case of larger firms). Second, variation in *Hratio* is greater for smaller stocks. Therefore, extreme *Hratio* observations in large stocks are smaller than extreme *Hratio* observations in small stocks.

[33] Note that sorting by aggregate *Hratio* is similar to sorting by change in the fraction of shares held by institutions. Specifically, if one divides the numerator and denominator of aggregate *Hratio* by the number of shares outstanding, the numerator and denominator become the fraction of shares held by institutions at the end of the quarter divided by the fraction of shares held at the beginning of the quarter.

[34] The *F*-statistics reported in the last row of Table 6 are based on the time-series of the 83 cross-sectional means.

sectional variation in the *change* in the fraction of shares held by institutional investors is positively related to lag returns, even when controlling for other security characteristics.

E. Ignoring Capitalization when Forming Institutional Demand Portfolios

In a recent paper, Cai and Zheng (2004) examine momentum trading by sorting securities into deciles based on the change in the fraction of shares held by institutions.[35] Thus, Cai and Zheng's method is similar to the method used to create Table 3, but does not control for capitalization. Their results suggest that institutional momentum trading is primarily limited to lag winners. For example, over months -2 to -12, securities in the fifth institutional demand decile underperformed the decile of securities most heavily sold by institutions (see their Table 4). As noted above, however, *absolute* changes in fraction of shares held by institutions are positively correlated with current capitalization, e.g., it is more common for a large security to move from 50 to 55 percent institutional ownership than a small security to move from 3 to 8 percent institutional ownership. As a result, sorting on changes in institutional ownership results in larger securities in the extreme portfolios and smaller securities in the middle portfolios. As noted above, such comparisons may be misleading because larger securities tend to have larger lag returns than smaller securities.

I repeat the Cai and Zheng (2004) method by sorting securities into institutional demand deciles ignoring capitalization and find, consistent with the above argument, securities in the middle "demand" portfolios are significantly smaller than securities in the extreme demand portfolios. For example, securities in the fifth demand decile are, on average, from the 29th capitalization percentile, while those securities in the decile most heavily purchased (sold) by institutions are from the 60th (56th) capitalization percentile. Not surprisingly, therefore, given the positive relation between size and lag returns (see Table 2), securities in the fifth demand portfolio average lower lag annual returns (by over 6 percent, on average) than securities in the lowest demand portfolio.[36]

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[35] Cai and Zheng (2004) examine both time-series momentum trading and cross-sectional momentum trading. I focus only on their cross-sectional tests (see footnote 2).
[36] Detailed results are not reported to conserve space.

F. Discussion

The results in this section demonstrate that a number of factors drive differences between the empirical results in the current study (Tables 3 and 4) and those reported in previous studies: (1) *GTW* and *Hratio* primarily measure momentum trading in the largest capitalization securities, (2) *GTW* and *Hratio* measure average, rather than aggregate, institutional demand, (3) disagreements between the sign of portfolio weight changes (in *GTW*) and the sign of position changes (in the other measures), and (4) the lack of independence between current capitalization and both lag returns and the absolute value of measures of institutional demand (e.g., the change in the fraction of shares held by institutions or *Hratio*). Moreover, the results in this section demonstrate that, once controlling for these factors, alternative methods yield results qualitatively identical to the results in this study (Tables 3 and 4).

There is nothing inherently wrong with examining momentum trading in a given value-weighted portfolio, if that is the goal of the study. The *GTW* metric, in particular, is a simple, intuitive metric – the lag return difference between the portfolio the manager holds at the end of the quarter and the portfolio the manager held at the beginning. Specifically, the *GTW* metric is well-suited to examine whether an institutional investor's momentum trading may help explain their portfolio's performance. Problems arise, however, when value-weighted metrics are: (1) used to examine the possibility that institutional momentum trading may contribute to cross-sectional return patterns and, (2) directly compared to equal-weighted metrics. That is, most of the work in this area is motivated by the possibility that institutional momentum trading may contribute to cross-sectional patterns in stocks returns, e.g., drive the price of lag winners too high and the price of lag losers too low.[37] Such *cross-sectional* return patterns, however, are nearly uniformly evaluated on an equal-weighted basis. Evidence of stock return momentum, for example, is typically derived from a comparison of subsequent returns of an equal-weighted portfolio of lag winners with an equal-weighted portfolio of lag losers (e.g., Jegadeesh and Titman, 1993). As a result, inferences regarding

[37] For instance, Lakonishok, Shleifer, and Vishny (1992, p. 24) note, "To see if institutional investors' trades influence stock prices, we empirically examine the trading patterns of institutional investors, focusing in particular on the prevalence of herding and positive-feedback trading, which are associated with the popular belief that institutional investors destabilize stock prices."

institutional investors' potential contribution to cross-sectional return patterns based on value-weighted metrics are inappropriate.[38] Because the *GTW* metric primarily measures momentum trading in the very largest of stocks, for example, one cannot conclude that a small *GTW* metric means that institutional investors do not contribute to cross-sectional return patterns.

Although the present study makes clear that direct comparisons of value-weighted and equal-weighted metrics are inappropriate, previous research has not made that distinction and, as a result, concluded that differences across studies are driven by differences in samples or aggregation techniques. For example, Badrinath and Wahal (2002) conclude that other cross-sectional tests of institutional momentum trading that erroneously conclude institutional investors do momentum trade, do so because they focus only on subsets of institutions (e.g., Chen, Hong, and Stein, 2002) or because they aggregate institutional ownership (e.g., Nofsinger and Sias), thereby obscuring the relation between changes in ownership by individual institutions and lag returns. In contrast, the results in the present study demonstrate that differences across studies are instead driven by the differences listed in the first paragraph of this section.

In addition, the *GTW* metric cannot be used to test whether institutional trading is potentially "destabilizing" because, although changes in portfolio weights are appropriate measures of an institution's demand for a security, changes in portfolio weights are not an appropriate measure of the potential effect of institutional demand on security returns. For example, an institution buying a security that recently increased in value contributes to, rather than offsets, institutional momentum trading in that security, even if the institution is not buying as much of that security as other securities (i.e., decreasing the portfolio weight). Last, because the *GTW* metric is averaged over institutions, one cannot interpret the results as reflecting aggregate institutional demand for a security. As noted in the previous paragraph, Badrinath and Wahal

[38] For example, based on the (implicitly) value-weighted *GTW* and *Hratio* metrics, Badrinath and Wahal, (2002) conclude that institutional momentum trading cannot contribute to cross-sectional patterns such as stock return momentum. Specifically, the authors conclude the lack of evidence of institutional momentum trading, "…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. Regardless, the small magnitude of aggregate momentum trading alleviates the concern that institutional traders generally destabilize stock prices." In addition, the authors' test implications of the Hong and Stein (1999) model that attempts to explain just such cross-sectional return patterns.

(2002) argue that averaging is superior to aggregation because aggregation, "…obscures the correlation between changes in individual portfolio holdings and past returns." Given the goal of the study is to examine whether institutional trading has the potential to impact security prices, averaging across managers is more likely to obscure the relation than aggregating over managers. Consider, for instance, a situation where a small institution sells 1,000 shares representing 1 percent of their portfolio while one large institution purchases 100,000 shares representing 1 percent of their portfolio – the former does not fully offset the latter. In sum, although the *GTW* metric is an appropriate measure of the extent to which an investor engages in momentum trading in their portfolio, it is an inappropriate measure of institutions' aggregate demand and the potential for that demand to contribute to cross-sectional return patterns.

The *Hratio* metric faces additional limitations. First, managers are more likely to make no change, completely exit, or establish a position in a small security than a large security. Because small securities average substantially smaller lag returns than large securities (see Table 2), lag returns for the no-change, entry and exit categories will tend to be smaller than lag returns for the other *Hratio* categories, regardless of the relation between lag returns and institutional demand. In addition, because *Hratio* is averaged over managers-security-quarter observations, *Hratio* does not reflect aggregate institutional demand. Moreover, because small managers are more likely to make no change to a holding, completely exit a security, or enter a security, small managers play a more important role in the no-change group as well as the extreme *Hratio* categories. Last, because *Hratio* pools observations across both institutions and securities, most stock-quarter observations appear multiple times in multiple categories, making inference problematic. Assume, for example, there is only one security. If three institutions completely exit the security (each selling 100 shares) and a fourth institution enters the security (buying 100 shares), the stock-quarter will contribute three observations to the exit category and one observation to the entry category. Although both the number of institutions holding shares and the fraction of shares held by institutions declined for this security, the *average* return for the entry and exit categories will not differ. Thus, it is possible for entry and exit category returns to be equal even if institutional investors momentum trade.

As noted above, regressions of changes in institutional ownership on lag returns yield results largely consistent with those reported in this study. Nonetheless, given absolute changes in institutional ownership are positively correlated with capitalization, larger stocks will play a larger role (i.e., account for more of the extreme observations) than smaller stocks in such regressions. Similarly, positive correlation between absolute changes in institutional ownership and capitalization means that when securities are simply sorted by changes in institutional ownership, large firms will play a more important role in the top and bottom groups and small firms will play a more important role in the middle groups. Because small firms average lower lag returns than large firms, inferences are misleading.

The reader may be tempted to infer that institutional momentum trading is relatively unimportant because it is weakest in those stocks that account for most institutional trading (i.e., large capitalization securities). This is likely not the case, however, for a number of reasons. First, all the tests reveal some evidence of short-term (e.g., lag quarterly) aggregate institutional momentum trading in large capitalization securities (e.g., Tables 3, 4, Panel F in Table 5, and Panel B of Table 6). Second, few large capitalization securities are extreme lag losers. The results in Panel D of Table 4 demonstrate, for example, only 1.13 percent of the securities are in both the large capitalization quintile and the extreme loser quintile. The results in Panel D also reveal, however, that institutions (in aggregate) do sell the few large securities that are extreme losers. Most important (as noted above), however, the return patterns that primarily motivate the examination of investors' momentum trading patterns (i.e., momentum and reversal patterns in stock returns; the process by which information is incorporated into security prices; and the potential to destabilize asset prices), are almost always evaluated though equal-weighted portfolios.

V. Conclusions and Suggestions for Future Work

Despite directly observable changes in ownership structure and returns, previous tests of institutional momentum trading reach vastly different conclusions. These differences primarily arise from differences in methods. Once accounting for these differences, I find strong evidence that institutions momentum trade. Moreover, assuming the primary goal of these tests is to examine the possibility that institutional trading patterns may influence cross-sectional patterns in security returns, then tests that equally-weight across securities, aggregate over managers, and control for correlation between the absolute value of measures of institutional demand and capitalization are the most theoretically justified.

Contrary to most recent work, this study demonstrates that institutional demand is strongly related to lag returns for most securities. As noted in the introduction, a number of hypotheses have been proffered to explain why institutions may engage in such behavior including overreaction to information, underreaction to information, agency problems in the money management industry, the attraction to securities with larger capitalizations, the use of stop-loss orders, and institutions offsetting the contrarian trading of individual investors. Although beyond the scope of the current study, future work should attempt to determine if any (or some combination) of these hypotheses explain institutional investors' behavior. In addition, researchers should reconsider the possibility that institutional investors' momentum trading contributes to cross-sectional return patterns (e.g., momentum and reversals in stock prices).

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TABLE 1
Summary of Empirical Institutional Momentum Trading Studies

Study	Sample	Evidence of Momentum Trading?
Cai and Zheng 2004, *Finance Research Letters*	All institutions (13F) 1981-1996	Weak (limited to buying of lag winners)
Bennett, Sias, and Starks 2003, *Review of Financial Studies*	All institutions (13F) 1983-1997	Yes
Gibson and Safieddine 2002, *Journal of Portfolio Management*	All institutions (13F) 1980-1994	No
Chen, Hong, and Stein 2002, *Journal of Financial Economics*	582-8,950 mutual funds 1979-1998	Yes
Badrinath and Wahal 2002, *Journal of Finance*	All institutions (13F) 1987-1995	No
Gompers and Metrick 2001, *Quarterly Journal of Economics*	All institutions (13F) 1980-1996	No
Nofsinger and Sias 1999, *Journal of Finance*	All institutions (13F) NYSE only, 1977-1996	Weak (limited to half of the capitalization deciles)
Wermers 1999, *Journal of Finance*	400-2,400 mutual funds 1974-1994	Weak (primarily limited to two smallest cap. quintiles)
Falkenstein 1996, *Journal of Finance*	2,500 mutual funds 1991-1992	No
Grinblatt, Titman, and Wermers 1995, *American Economic Review*	274 mutual funds 1974-1984	Weak (limited to purchase of large capitalization lag winners)
Lakonishok, Shleifer, and Vishny 1992, *Journal of Financial Economics*	769 pension funds 1985-1989	Weak (limited to sale of small capitalization lag losers)

TABLE 2
Descriptive Statistics

	Average	Minimum	25th percentile	75th percentile	Maximum
	Panel A: Average across Institutions				
Number of Institutional Investors	1,098	552	800	1,363	1,828
Number of Securities in Portfolio	250	206	235	266	283
Value of Portfolio ($millions)	2,456	878	1,368	3,500	5,285
	Panel B: Average across Securities				
Number of Securities	5,229	3,881	4,766	5,780	6,442
%Shares Held by Institutions	26.34%	16.78%	20.99%	30.29%	40.85%
%Shares Held by Capitalization					
Small Capitalization	7.38%	3.80%	5.67%	9.12%	11.69%
Capitalization Quintile 2	14.61%	7.58%	11.33%	17.82%	23.68%
Capitalization Quintile 3	21.55%	12.93%	18.36%	28.95%	41.94%
Capitalization Quintile 4	36.69%	23.14%	28.23%	42.14%	60.93%
Large Capitalization	48.49%	35.96%	40.92%	53.79%	66.34%

	Panel C: Average Market-adjusted Return Over:		
	Previous Quarter	**Previous 6 Months**	**Previous Year**
Small Capitalization	-4.51%	-9.61%	-20.15%
Capitalization Quintile 2	0.26%	0.48%	-0.17%
Capitalization Quintile 3	2.13%	4.28%	8.65%
Capitalization Quintile 4	3.13%	6.73%	14.58%
Large Capitalization	2.68%	5.72%	13.41%

For each quarter between the first quarter of 1983 and the fourth quarter of 2003, I compute the number of institutional investors as well as the cross-sectional averages of the number of securities within each manager's portfolio and the value of each manager's portfolio. Panel A reports the time-series mean, minimum, 25th percentile, 75th percentile, and maximum of these cross-sectional averages. Panel B reports the time series mean, minimum, 25th percentile, 75th percentile, and maximum of the cross-sectional averages of the fraction of shares held by institutional investors each quarter. In addition, results are partitioned by capitalization quintile. Panel C reports the time-series average of the cross-sectional mean market-adjusted return over the previous quarter, six-months, or year for securities within each capitalization quintile.

TABLE 3
Lag Market-Adjusted Returns (in percent) for Portfolios Sorted by Aggregate Institutional Demand

Portfolio	Change in % Shares Held by Institutions	Number Observations	Over Same Quarter	Over Previous Quarter	Over Previous 6 Months	Over Previous Year
Panel A: Capitalization-Stratified Sample						
Decrease	-4.04	1,132	-4.21	-3.59	-4.86	-3.80
Quintile 2	-0.41	1,134	-2.04	-0.48	-0.96	-0.72
No Change	0.00	187	-1.90	-2.55	-6.37	-14.77
Quintile 4	0.52	1,386	0.39	1.69	2.79	4.56
Increase	4.34	1,389	7.15	4.92	8.82	14.20
***F*-statistic**[a]			26.24**	16.97**	26.74**	35.82**
***F*-statistic**[b]			33.17**	18.69**	24.08**	19.58**
Panel B: Small Stocks						
Decrease	-2.70	241	1.97	-8.61	-15.92	-38.02
Quintile 2	-0.11	241	1.03	-4.46	-9.74	-21.28
No change	0.00	154	-1.23	-3.83	-8.81	-19.82
Quintile 4	0.14	204	3.57	-3.13	-7.74	-17.80
Increase	2.54	205	9.31	-1.24	-3.62	-10.56
***F*-statistic**[a]			7.32**	4.80**	7.68**	9.32**
Panel C: Capitalization Quintile 2						
Decrease	-3.55	235	-3.05	-5.24	-8.62	-13.10
Quintile 2	-0.28	236	-3.15	-0.10	-0.56	-1.89
No change	–	–	–	–	–	–
Quintile 4	0.29	273	-0.84	1.78	2.75	-3.05
Increase	3.44	273	7.23	3.80	6.88	9.37
***F*-statistic**[b]			23.36**	13.57**	17.79**	15.63**
Panel D: Capitalization Quintile 3						
Decrease	-4.52	221	-6.89	-4.04	-5.00	-3.37
Quintile 2	-0.49	221	-3.58	0.02	0.04	2.79
No change	–	–	–	–	–	–
Quintile 4	0.55	299	-0.63	3.17	5.75	10.34
Increase	4.97	299	7.88	7.17	12.60	20.25
***F*-statistic**[b]			38.64**	13.35**	10.77**	6.09**
Panel E: Capitalization Quintile 4						
Decrease	-5.24	212	-8.48	-1.11	1.28	10.83
Quintile 2	-0.63	212	-3.23	0.69	2.56	8.56
No change	–	–	–	–	–	–
Quintile 4	0.76	310	0.02	2.86	5.42	10.70
Increase	5.60	311	7.06	7.90	14.66	26.07
***F*-statistic**[b]			70.81**	23.30**	21.13**	5.37**
Panel F: Large Stocks						
Decrease	-4.43	222	-6.35	1.69	6.05	18.64
Quintile 2	-0.58	223	-1.91	1.86	4.13	10.84
No change	–	–	–	–	–	–
Quintile 4	0.70	300	0.77	2.08	3.83	8.44
Increase	4.43	301	4.95	4.68	8.61	17.07
***F*-statistic**[b]			119.38**	6.46**	5.94**	6.51**

TABLE 3 (continued)
Lag Market-Adjusted Returns (in percent) for Portfolios Sorted by Aggregate Institutional Demand

Each quarter, stocks within each capitalization quintile are sorted into five groups by the change in the fraction of shares held by institutional investors. The no change group consists of securities that have no change in the fraction of shares held by institutions. Securities that experience a decline in the fraction of share held by institutions are partitioned into two equal-sized groups (within each capitalization quintile) based on the change in the fraction of shares held by institutions. Similarly, securities that experience an increase in the fraction of shares held by institutions are partitioned into two equal-size groups (within each capitalization quintile) based on the change in the fraction of shares held by institutions. The first and second columns report the time-series mean of the 83 cross-sectional average fraction of shares outstanding moving to institutional investors, and average number of securities within each group, respectively. The next four columns report the time-series mean of the 83 cross-sectional average market-adjusted (CRSP value-weighted index) returns for the securities in each portfolio over the same quarter, the previous quarter, the previous six months, and the previous year, respectively. *F*-statistics are based on the null hypothesis that the time-series of cross-sectional average returns do not differ across the portfolios. Panel A reports results for the capitalization-stratified sample. Panels B through F report results by capitalization quintile. Portfolios that average less than 50 observations each quarter are excluded from the analysis.

[a] The *F*-statistic is based on the hypothesis returns are equal across the five groups.

[b] The *F*-statistic is based on the hypothesis returns are equal across the top two and bottom two groups (i.e., excludes the no change group).

** indicates statistical significance at the 1 percent level; * at the 5 percent level.

TABLE 4

Adjusted Changes in Ownership for Securities Sorted Independently on Lag Returns and Capitalization

	Losers	Quintile 2	Quintile 3	Quintile 4	Winners	*F*-statistic
	Panel A: Sorted by Contemporaneous Quarterly Return					
	Contemporaneous Market-adjusted Quarterly Returns (fraction of observations)					
Small Firms	-33.60 (5.43)	-12.30 (3.63)	-2.15 (3.07)	8.47 (3.01)	53.87 (4.85)	
Quintile 2	-32.21 (4.63)	-12.16 (3.98)	-2.09 (3.64)	8.37 (3.57)	41.02 (4.19)	
Quintile 3	-31.35 (3.20)	-12.20 (4.01)	-2.18 (3.85)	8.41 (3.87)	37.12 (4.07)	
Quintile 4	-30.44 (3.47)	-12.04 (4.11)	-2.09 (4.26)	8.41 (4.34)	32.64 (3.81)	
Large Firms	-28.07 (2.24)	-11.75 (4.28)	-2.03 (5.20)	8.16 (5.21)	27.88 (3.06)	
	Adjusted Change in Fraction of Shares Held by Institutions					
Small Firms	-3.03	-0.55	1.61	1.08	2.19	35.54**
Quintile 2	-3.78	-0.42	0.41	0.69	3.43	112.30**
Quintile 3	-4.85	-1.00	-0.04	1.04	4.95	287.03**
Quintile 4	-5.27	-0.95	0.01	1.31	4.39	383.75**
Large Firms	-4.34	-0.90	0.09	1.13	2.57	288.93**
	Panel B: Sorted by Lag Quarterly Return					
	Market-adjusted Lag Quarterly Returns (fraction of observations)					
Small Firms	-34.52 (6.75)	-12.30 (3.92)	-2.14 (3.05)	8.45 (2.72)	47.91 (3.56)	
Quintile 2	-31.19 (4.69)	-12.03 (4.07)	-2.04 (3.68)	8.48 (3.54)	43.20 (4.03)	
Quintile 3	-30.07 (3.85)	-12.08 (4.04)	-2.06 (3.89)	8.54 (3.89)	41.42 (4.34)	
Quintile 4	-28.65 (2.92)	-11.87 (3.98)	-1.99 (4.26)	8.56 (4.44)	37.18 (4.41)	
Large Firms	-26.11 (1.76)	-11.54 (4.02)	-1.90 (5.14)	8.37 (5.41)	30.94 (3.66)	
	Adjusted Change in Fraction of Shares Held by Institutions					
Small Firms	-3.55	0.87	1.50	2.06	2.48	42.96**
Quintile 2	-4.47	-0.30	0.64	1.30	3.66	161.23**
Quintile 3	-4.47	-0.95	0.08	1.20	3.63	282.48**
Quintile 4	-3.49	-0.98	-0.18	0.54	2.74	296.01**
Large Firms	-1.58	-0.25	0.06	0.18	0.55	42.00**
	Panel C: Sorted by Lag Six-month Return					
	Market-adjusted Returns over Previous Six Months (fraction of observations)					
Small Firms	-47.61 (7.27)	-18.77 (4.10)	-3.91 (2.97)	11.64 (2.61)	66.34 (3.06)	
Quintile 2	-43.59 (4.78)	-18.35 (4.12)	-3.73 (3.68)	11.71 (3.49)	66.19 (3.90)	
Quintile 3	-41.89 (3.80)	-18.19 (4.10)	-3.71 (3.82)	11.83 (3.83)	64.78 (4.38)	
Quintile 4	-40.04 (2.67)	-17.95 (3.91)	-3.64 (4.29)	11.77 (4.46)	59.39 (4.66)	
Large Firms	-37.08 (1.47)	-17.37 (3.78)	-3.50 (5.24)	11.52 (5.61)	48.41 (3.99)	
	Adjusted Change in Fraction of Shares Held by Institutions					
Small Firms	-4.09	0.91	1.70	2.83	4.02	69.57**
Quintile 2	-4.92	-0.70	0.65	2.19	4.05	215.28**
Quintile 3	-4.76	-1.20	0.00	1.19	4.19	346.47**
Quintile 4	-3.66	-1.03	-0.22	0.32	2.78	271.85**
Large Firms	-1.55	-0.10	0.09	0.07	0.28	34.51**
	Panel D: Sorted by Lag Annual Return					
	Market-adjusted Returns over Previous Year (fraction of observations)					
Small Firms	-66.36 (8.02)	-29.80 (4.32)	-7.79 (2.90)	15.79 (2.38)	95.20 (2.47)	
Quintile 2	-61.53 (4.92)	-28.33 (4.17)	-7.48 (3.56)	15.86 (3.35)	102.94 (3.71)	
Quintile 3	-59.30 (3.61)	-28.98 (4.07)	-7.39 (3.78)	16.19 (3.75)	104.79 (4.40)	
Quintile 4	-56.79 (2.31)	-28.44 (3.91)	-7.21 (4.31)	16.14 (4.52)	100.10 (4.90)	
Large Firms	-53.80 (1.13)	-27.38 (3.54)	-6.91 (5.45)	15.73 (6.01)	84.25 (4.52)	
	Adjusted Change in Fraction of Shares Held by Institutions					
Small Firms	-3.58	0.78	1.78	3.28	4.45	50.28**
Quintile 2	-4.40	-0.77	1.19	1.80	4.02	177.61**
Quintile 3	-4.26	-0.97	-0.04	0.94	3.61	228.50**
Quintile 4	-2.75	-0.68	-0.25	0.32	1.70	136.85**
Large Firms	-0.62	0.05	0.04	0.06	-0.11	5.32**

TABLE 4

Adjusted Changes in Ownership for Securities Sorted Independently on Lag Returns and Capitalization

Each quarter, securities are sorted into quintiles by beginning-of-quarter capitalization. Securities are then independently sorted (each quarter) by contemporaneous quarter return (Panel A), lag quarter return (Panel B), lag six-month return (Panel C), or lag annual return (Panel D). The first five rows in each panel report the time-series average of the cross-sectional mean market-adjusted return (in percent) for securities in that size/performance group and the fraction of total observations accounted for by securities within that size/performance group (in parentheses). The second five rows in each panel report the time-series mean of the cross-sectional average adjusted change in the fraction of shares held by institutions for securities within each size/performance classification. The adjusted change in the fraction of shares held by institutions is defined as the raw change that quarter less the mean change that quarter for securities within the same capitalization quintile divided by the average fraction of shares held by institutions that quarter for securities within the same capitalization quintile. The *F*-statistic reported in the last column tests for equality across the five performance quintiles within each capitalization quintile and is based on the time-series of cross-sectional averages.
** indicates statistical significance at the 1 percent level; * at the 5 percent level.

TABLE 5
Analysis of *GTW* Measure

	Number Obs. (% mixed signs)	Absolute Change in Portfolio Weight (in %)	Mean *GTW* Contribution Based On: Return Over Same Quarter	Return Over Previous Quarter	Return Over Previous 6 Months	Return Over Previous Year
	Panel A: All Observations (observation weighted, % of basis points)					
All Obs.	23,145,675		0.090	-0.013	-0.032	-0.106
	(29.0)		(10.88)**	(-0.28)	(-1.15)	(-2.38)*
	Panel B: All Observations by Capitalization Quintile (observation-weighted, % of basis points)					
Small Firms	394,534	0.020	0.151	-0.015	0.029	0.048
	(56.0)		(1.70)	(-0.11)	(1.04)	(0.93)
Quintile 2	881,369	0.037	0.213	0.069	0.130	0.135
	(44.1)		(4.83)**	(2.89)**	(3.45)**	(2.81)**
Quintile 3	1,991,101	0.058	0.219	0.110	0.183	0.216
	(33.4)		(6.22)**	(4.78)**	(5.33)**	(4.74)**
Quintile 4	4,369,686	0.084	0.110	0.009	0.020	0.049
	(27.8)		(8.87)**	(2.27)*	(2.89)**	(2.51)*
Large Firms	11,508,985	0.158	0.059	-0.039	-0.085	-0.206
	(27.2)		(5.98) **	(-3.66)**	(-4.81)**	(-3.75)**
	Panel C: Restricted Sample (observation-weighted, % of basis points)					
Restricted Sample	16,429,330		0.134	-0.008	-0.033	-0.127
	(0.0)		(11.76)**	(0.85)	(-0.28)	(-1.67)
	Panel D: Restricted Sample by Capitalization Quintile (observation-weighted, % of basis points)					
Small Firms	173,503	0.033	0.225	0.147	0.200	0.225
	(0.0)		(1.49)	(2.93)**	(3.00)**	(2.43)*
Quintile 2	493,085	0.051	0.337	0.164	0.324	0.370
	(0.0)		(6.40)**	(5.14)**	(5.48)**	(4.86)**
Quintile 3	1,325,353	0.074	0.343	0.178	0.284	0.384
	(0.0)		(7.89)**	(6.82)**	(7.34)**	(6.10)**
Quintile 4	3,153,270	0.105	0.167	0.021	0.028	0.064
	(0.0)		(10.46)**	(3.26)**	(3.51)**	(3.21)**
Large Firms	11,284,119	0.200	0.090	-0.048	-0.106	-0.262
	(0.0)		(6.64) **	(-3.13)**	(-4.51)**	(-3.48)**
	Panel E: Aggregate *GTW* (averaged over quarters, basis points)					
All Obs.	83		21.718	7.521	11.246	8.934
			(11.10)**	(4.48)**	(3.85)**	(1.40)
	Panel F: Aggregate *GTW* by Capitalization Quintile (averaged over quarters, basis points)					
Small Firms	83		0.058	0.048	0.078	0.112
			(4.59)**	(5.29)**	(6.27)**	(5.29)**
Quintile 2	83		0.429	0.263	0.475	0.700
			(7.08)**	(7.92)**	(7.23)**	(7.61)**
Quintile 3	83		1.857	1.258	2.145	3.043
			(8.35)**	(10.89)**	(9.76)**	(10.07)**
Quintile 4	83		4.522	3.506	6.147	8.529
			(11.76)**	(11.92)**	(11.72)**	(10.12)**
Large Firms	83		14.852	2.445	2.402	-3.449
			(9.13)**	(1.73)	(0.98)	(-0.56)

TABLE 5 (continued)
Analysis of *GTW* Measure

Panel A reports the pooled cross-sectional time-series average product of the 23,145,675 manager-security-quarter contributions to the *GTW* measure. The *GTW* contribution for each manager-security-quarter position is the product of the change in the manager's portfolio weight over the quarter and the security's market-adjusted return measured over the same quarter (third column), previous quarter (fourth column), previous six months (fifth column), or previous year (sixth column). Reported contributions are in percent of basis points. The *t*-statistics (reported in parentheses) are based on the time-series standard error of the quarterly cross-sectional averages. The first column reports the number of observations and the fraction of observations (in parentheses) where the sign of the change in the manager's portfolio weight differs from the sign of the change in the manager's position (e.g., buying, but decreasing portfolio weight). Panel B partitions the results in Panel A by capitalization quintile. The second column in Panel B reports the pooled cross-sectional time-series average absolute value of the change in the portfolio weight (in percent). Panels C and D repeat the analysis in Panels A and B limiting the sample to manager-security-quarter observations where the sign of the change in the portfolio weight is the same as the sign of the change in the manager's position (the "restricted sample"). Panel E reports the aggregate *GTW* measure – representing the sum of the products of the change in the aggregate institutional portfolio weights (i.e., institutional holdings aggregated across all managers) and returns measured over the same quarter, previous quarter, previous six months, or previous year. Panel F reports the average contribution to the aggregate *GTW* by capitalization quintile (summing averages in Panel F yields the average reported in Panel E).

TABLE 6
***Hratio* Analysis**

Panel A: *Hratio* portfolios

	Number Obs.	Cap. Percentile	Manager Size Percentile	Average Market-adjusted Return (in %) Over: Same Quarter	Previous Quarter	Previous 6 Months	Previous Year	Fraction Positive (return>market return) Same Quarter	Previous Quarter	Previous 6 Months	Previous Year
Entry	2,560,619	0.78	0.69	6.39	5.36	10.82	22.04	56.0	53.5	54.2	54.5
High-Buy	2,383,461	0.83	0.79	1.12	3.39	7.94	18.38	49.1	52.1	53.3	54.1
Med-Buy	1,642,568	0.84	0.78	0.70	1.89	4.70	11.99	48.8	50.5	51.5	52.6
Low-Buy	3,020,554	0.86	0.79	0.96	1.53	3.33	8.21	49.9	50.8	51.6	52.2
No change	4,599,063	0.75	0.72	0.34	0.54	1.23	3.30	47.7	48.1	47.8	46.9
Low-Sell	3,180,015	0.87	0.75	1.17	1.55	3.04	6.93	50.8	51.5	51.8	51.8
Med-Sell	1,752,727	0.86	0.76	1.48	2.13	4.51	10.77	50.6	51.4	51.7	51.8
High-Sell	1,811,687	0.84	0.78	0.76	1.76	4.54	12.80	48.0	49.3	49.7	50.4
Exit	2,194,981	0.78	0.69	-2.73	0.45	2.98	10.73	42.1	46.2	46.5	47.4

Panel B: Average Lag 6-Month Market-Adjusted Returns and Fraction Positive for Aggregate *Hratio* Quintiles by Capitalization

	Small firms Mkt.-adj. Return	Fraction Positive	Cap. Quintile 2 Mkt.-adj. Return	Fraction Positive	Cap. Quintile 3 Mkt.-adj. Return	Fraction Positive	Cap. Quintile 4 Mkt.-adj. Return	Fraction Positive	Large Firms Mkt.-adj. Return	Fraction Positive
High *Hratio*	-2.85	36.50	14.03	51.07	22.14	57.76	22.27	60.42	11.89	56.93
Quintile 2	-8.50	32.75	1.06	43.19	5.71	47.66	7.38	52.51	5.10	53.09
Quintile 3	-8.87	32.58	-0.70	41.16	0.62	43.98	3.29	49.60	3.66	52.47
Quintile 4	-13.40	28.61	-5.60	35.53	-2.38	39.89	1.12	45.90	4.03	54.25
Low *Hratio*	-15.24	26.82	-6.36	34.01	-4.51	36.24	-0.19	41.70	4.05	50.08
***F*-statistic**	8.76**	7.65**	27.29**	20.59**	43.37**	36.99**	41.39**	32.02**	11.74**	6.48**

Hratio is defined for each manager-security-quarter observation as the ratio of the number of shares held at the end of the quarter to the number of shares held at the beginning of the quarter. Manager-security-quarter observations are then sorted into nine groups: entry ($H_{i,j,t}$> 0, $H_{i,j,t\text{-}1}$=0), high-buy ($Hratio_{i,j,t}$>1.3), medium-buy (1.3≥$Hratio_{i,j,t}$>1.1), low-buy (1.1≥$Hratio_{i,j,t}$>1), no change ($H_{i,j,t}$=$H_{i,j,t\text{-}1}$), low-sell (1>$Hratio_{i,j,t}$≥0.9), medium-sell (0.9>$Hratio_{i,j,t}$≥0.7), high-sell (0.7>$Hratio_{i,j,t}$), and exit ($H_{i,j,t}$=0, $H_{i,j,t\text{-}1}$> 0). The first three columns in Panel A report the number of observations, average capitalization percentile, and average manager size percentile, respectively, for securities in that group. Capitalization and manager size percentiles are computed at the beginning of each quarter. The next four columns report the pooled cross-sectional time-series mean contemporaneous or lag market-adjusted (CRSP value-weighted) return for observations within each *Hratio* group. The last four columns report the fraction of market-adjusted returns in that category that are positive. Panels B reports the time-series mean of the cross-sectional average lag six-month market-adjusted return (and fraction of securities outperforming the market) for securities sorted into aggregate *Hratio* quintiles within each capitalization quintile. The aggregate *Hratio* for security *i* is computed as the ratio of the total number of shares held by institutions in aggregate at the end of the quarter to the total number of shares held by institutions at the beginning of the quarter. *F*-statistics reported in the last row are based on the null hypothesis that the time-series of cross-sectional averages do not differ across the aggregate *Hratio* portfolios. ** indicates statistical significance at the 1 percent level.