Is momentum caused by delayed overreaction?

Working paper

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January 2002

First draft: May 2001

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ABSTRACT. This paper tests competing behavioral explanations of momentum effects in stock returns, focusing on long-run patterns in returns and institutional ownership. I show that previously documented reversals in momentum profits—apparent evidence for delayed overreaction—disappear when returns are adjusted for differences in characteristics between winner and loser stocks, such as size, book-to-market, and trading volume. Moreover, breadth of institutional ownership increases (decreases) for stocks with positive (negative) past returns, and these changes do not revert in the long-run. Driven by these changes in breadth, there is also a positive relation between past returns and the share of institutional investor holdings. These persistent changes in institutional ownership indicate that winners (losers) are priced low (high) relative to fundamentals. Taken together the evidence suggests that underreaction, not delayed overreaction, is the most promising behavioral explanation of momentum effects.

Keywords: Momentum, breadth of ownership, institutional ownership, delayed overreaction, underreaction.

JEL classification: G14, G12
The momentum anomaly documented by Jegadeesh and Titman (1993) is one of the most intriguing empirical puzzles in finance. “Winner” stocks which have outperformed over the last 3-12 months continue to outperform over the following 12 months, “losers” continue to underperform. Existing asset pricing models fail to explain this effect. This has prompted some researchers to develop models based on limited rationality and investor misreaction. This literature shows that, in principle, underreaction as well as delayed overreaction could generate momentum. These two competing behavioral hypotheses have very different implications. The underreaction hypotheses predicts winners, for example, to be undervalued, whereas the delayed overreaction hypothesis predicts them to be overvalued.

There is yet relatively little research that explicitly tests these behavioral explanations of momentum against each other, but recent papers by Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) take a step in this direction. They examine long-horizon returns of momentum strategies and find that momentum profits revert at horizons of 3-5 years—consistent with the prediction of delayed overreaction models that momentum profits are transitory. Is delayed overreaction therefore the source of momentum profits? In this paper I argue that it is not. Instead, my results point to underreaction as the most promising behavioral explanation of momentum effects.

To distinguish among underreaction and delayed overreaction hypotheses I use several valuation indicators. The first and most conventional one is the long-horizon return. I re-examine the results of Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) and check whether their

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2 Grundy and Martin (2001) find that adjusting for dynamic exposure to the three Fama-French factors does not help to explain the mean return of momentum strategies. Other papers are partly more successful in linking momentum profits to risk. Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2001) present rational models capable of generating momentum effects. Empirically, Chordia and Shivakumar (2002) find that momentum is linked to realizations of macroeconomic variables. Ang, Chen, and Xing (2001) find a downside risk factor can explain at least a fraction of momentum profits. Ahn, Conrad, and Dittmar (2002) use nonparametric methods to estimate a stochastic discount factor that is able to price individual stock return momentum portfolios, but not industry momentum portfolios. The focus of this paper is on testing competing behavioral explanations, not on testing rational against behavioral explanations.

3 In Daniel, Hirshleifer, Subrahmanyam (1998) overconfidence, coupled with biased self-attribution, leads to delayed overreaction. In contrast, momentum arises mainly from underreaction due to conservatism bias in Barberis, Shleifer, and Vishny (1998), and due to slow information diffusion and bounded rationality of “newswatchers” and “momentum traders” in Hong and Stein (1999). Investors in Grinblatt and Han (2001) and Zuchel and Weber (2001) exhibit disposition effects, which also results in underreaction-type price patterns.
results are robust evidence against underreaction, or whether the reversals can perhaps be attributed to winner-loser differences in expected-return-related characteristics. Unfortunately, without an accepted pricing model for the cross-section of stock returns the power of such long-horizon returns tests to reject one of the competing hypotheses is limited. To obtain additional evidence I therefore look at other variables that could be informative about the direction of mispricing experienced by winners and losers.

In the second set of tests I build on the insight of Chen, Hong, and Stein (CHS) (2001) that breadth of ownership can be a valuation indicator. CHS show that if some investors face short-sales constraints, and they disagree on the valuation of an asset, the market price reflects the valuations of optimists, but not those of pessimists. This implies that overvalued stocks have a low breadth of ownership, as optimists are the only investors left holding it, while pessimists are sitting on the sidelines. CHS provide empirical support for this hypothesis. Applied to the momentum puzzle this means the following: if winners, for example, are undervalued, as the underreaction hypothesis predicts, then they should experience increases in breadth of ownership. In contrast, with delayed overreaction breadth should go down in response to a positive return shock—contemporaneously or at least soon after the shock.

Third, I look at changes in the share of outstanding equity held by institutions. The motivation of these tests is quite simple: if there is any mispricing, institutional investors should be those who exploit it, rather than individuals. A growing body of evidence supports the idea that, on average, institutional investors’ trades are more informed than individuals’ trades. Hence, if momentum were a delayed overreaction phenomenon, one would expect the more informed institutional investors to sell (buy) winners (losers) before reversals set in and transitory momentum profits vanish.

My findings reject delayed overreaction explanations of momentum. The long-horizon return tests reveal that reversals in momentum profits disappear when holding period returns are adjusted for winner-loser differences in characteristics such as size, trading volume, and, most importantly, book-to-market. Moreover, I show that the apparent role of trading volume in predicting whether momentum profits persist or revert in the long-run, uncovered by Lee and Swaminathan (2000), simply reflects the return premium for low volume (turnover) stocks reported in Datar, Naik, and
Radcliffe (1998), independent of the momentum effect. An intuitive interpretation of these results is that reversals in raw momentum profits can arise without delayed overreaction: stocks that experience large positive returns may become less risky (reflected in lower book-to-market) and more liquid (reflected in higher volume), and hence command a lower expected return once the initial momentum effect has subsided. Nevertheless, given the controversy about the source of the book-to-market effect, there is some ambiguity. It is perceivable, for example, that the book-to-market adjustment actually eliminates overreaction-induced mispricing effects, biasing these tests in favor of underreaction. In general, this ambiguity makes it hard to reject any of the hypotheses solely based on long-horizon return evidence.

However, alternative valuation indicators also reject the delayed overreaction story. From data on mutual fund stock holdings from 1980-2000 I calculate the Chen, Hong, and Stein (CHS) (2001) breadth of ownership measure. I find that breadth of ownership of winners increases contemporaneously with the return shock, as well as during the first four quarters after the shock, and these changes do not revert later on. For losers the opposite happens. Following the logic of the CHS model, this suggests that winners are bought by some previously sidelined pessimists because they are undervalued, and losers are sold by some of the optimists because they are overvalued—consistent with underreaction. I repeat the same analysis with quarterly data on institutional holdings over the period 1980-2000. This data set covers most institutional investors, not just mutual funds. The results are very much the same.

Using the latter data set, I also investigate changes in the share of institutional holdings in winners and losers. I find that, on balance, institutions buy winners from individuals and hold on to them, whereas they sell losers and stay away from them. This suggests that winners are undervalued and losers overvalued—consistent with underreaction. These results complements recent work by Cohen, Gompers, Vuolteenaho (2001). In firm-level vector autoregressions (VAR) they find that news about cash-flows is positively related to the future share of institutional ownership. By looking at simple event time averages I do not restrict the joint process of returns and institutional ownership as

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4 Fama and French (1993), arguing in favor of a risk-based explanation, and Lakonishok, Shleifer, and Vishny (1994), suggesting a mispricing explanation, started off the debate. To date this issue is not settled, see e.g. Vassalou (2001), and Daniel, Hirshleifer, and Subrahmanyam (2001) for recent contributions.
much as their VARs do, which may make it easier to detect whether the initial changes in ownership revert later on. Furthermore, my results show that changes in breadth actually seems to be the most important variable. I find that changes in institutional holdings in response to return shocks are driven by changes in breadth of ownership, not by changes in average holdings per institution.

Certainly, such rather indirect tests of competing theories of momentum have a drawback: the mechanism envisioned by CHS is perhaps not the only plausible reason for changes in breadth of ownership like those observed here. However, it turns out that the conclusions are similar under a variety of alternative stories. For example, if these changes in ownership really reflect some superior stock picking skills on the part of institutional investors, rather than the effect of differences in opinions, the implications are the same: winners (losers), attracting additional institutional buying (selling) are under- (over-) valued—consistent with underreaction. Further robustness checks show that the relationship between past returns and future changes in breadth of ownership are not driven by increased “attention” to stocks with large positive returns. Neither are the results driven by mechanical momentum investing by institutions. When I exclude institutions classified as momentum investors (based on their trades over the preceding four quarters), the positive relationship between changes in breadth and past returns remains intact. There is one alternative explanation, though, that could reconcile the patterns in breadth of institutional ownership with delayed overreaction. This would require that there be a sufficiently large number of institutions investing in overvalued winners and shunning undervalued losers—large enough to make breadth and aggregate institutional holdings in winners (losers) go up (down). While I cannot rule out this possibility, I note that it does not seem very plausible. It would mean that those investors with superior resources and best access to information trade worse than individuals, the residual group of investors in this data set. This would also be in conflict with evidence on inferior trading performance of individuals reported in Grinblatt and Keloharju (2000) and Barber and Odean (2000), among others.

In addition to the papers already referenced, this study is related to other work in this area that tests the implications of underreaction and/or delayed overreaction models. The evidence is mixed. Chan, Jegadeesh, and Lakonishok (1996) find little evidence that drifts in returns are subsequently reversed, except when large positive returns occur together without positive news about earnings. In a
related vein, Chan (2001) finds return continuations only when price movements are accompanied by public news. Hong, Lim, and Stein (2000) find that momentum profits are highest for small firms with low analyst coverage, which supports the underreaction hypothesis. Hvidkjaer (2000) examines microstructure data and finds evidence for persistent buying (selling) market-order overhang for winners (losers) after the time of portfolio formation, which he interprets as support for delayed overreaction models. Lewellen (2002) shows that size, book-to-market, and industry portfolios also exhibit momentum effects, but largely due to negative cross-serial correlations of their returns, which is not explained by underreaction models.

The remainder of the paper is organized as follows. Section I presents the data and describes the methodology. Section II presents the results on long-horizon returns of momentum strategies. Section III investigates changes in institutional ownership associated with momentum. Section IV discusses the results and evaluates alternative interpretations. Section V concludes.

I. Methodology and Data

In this section I outline the tests employed in this paper and provide the rationale for them. This is followed by a description of the data used in these tests, the test methodology, and some summary statistics

A. Hypotheses and tests

The objective in this paper is to test two competing behavioral hypotheses about the source of momentum in stock returns. The underreaction hypothesis predicts that prices adjust sluggishly to new information, hence stocks with positive (negative) recent returns are undervalued (overvalued). This is the main driving force of momentum in models like Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999). In contrast, the delayed overreaction hypothesis predicts that winners (losers) are overvalued (undervalued), and momentum arises because this misvaluation even gets worse before prices finally revert back to fundamental values. Such price patterns are generated by the model of Daniel, Hirshleifer, and Subrahmanyam (1998), for example. As these hypotheses make diametrically opposed predictions about the direction of deviations from fundamental value, the key to
discriminating between them is to find appropriate valuation indicators. For reasons explained below I use three such indicators: long-run returns, changes in breadth of ownership, and changes in the share of institutional ownership.

The most common way of tackling this question is to look at long-horizon returns. Future returns of overvalued stocks should be relatively low, whereas undervalued stocks should exhibit positive abnormal returns. Hence, the delayed overreaction hypothesis predicts that winners should do worse than losers once the initial momentum effect has subsided. This is what Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) find—in apparent contradiction to underreaction theories of momentum. Yet, there is a well-known problem in evaluation such long-horizon returns: the results tend to be sensitive to the choice of benchmarks for expected returns. In other words, the fact that winners earn lower returns than losers in the long-run could be due to the fact that winners are less risky or more liquid and hence carry a lower return premium. To check the robustness of the long-horizon reversals evidence I repeat their tests using a different set of benchmarks than those employed in above studies, and I also use UK data in addition to the standard US data sets.

The second set of tests exploits the insight of Chen, Hong, and Stein (CHS) (2001) that decreases in breadth of ownership may indicate overvaluation. In their model investors hold different beliefs about the fundamental value of an asset, and some investors are restricted from selling it short. As a consequence, when the number of investors with long positions in the asset is relatively low, it indicates that more pessimistic investors—unable to sell short—sit on the sidelines, and the market price reflects only the valuations of optimists. Consistent with this hypothesis, CHS find that decreases in breadth of mutual fund ownership predict low future returns in the cross-section. Several recent papers find additional supporting evidence. Diether, Malloy, and Scherbina (2002) report that high dispersion in opinions, measured by analyst disagreement, forecasts low future returns. Jones and Lamont (2001) find that stocks which are more expensive to short have lower subsequent returns.

This theory has interesting implications for the question addressed in this paper. Assuming that the CHS model holds, the underreaction hypothesis predicts that changes in breadth of ownership

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5 This issue is intensely debated in the large literature on inference in long-horizon event studies. See e.g. Fama (1998) and Loughran and Ritter (2000) and references therein.
should be positively related to past returns, as undervaluation of winners prompts some previously sidelined pessimists to buy, and overvaluation of losers forces some optimists to move to the sidelines. In contrast, the delayed overreaction hypothesis predicts a negative relationship. Moreover, the underreaction hypothesis predicts that changes in breadth occurring in response to past returns should persist: once the initial mispricing has been corrected via momentum there is no reason why these changes in breadth should revert substantially afterwards—if they did, it would cast doubt about the underreaction explanation. To capture such long-run effects I test these predictions by looking at the relationship between past returns and changes in breadth at horizons of up to five years.

Finally, in the third set of test I look at the share of outstanding equity held by institutional investors. The rationale here is that institutional investors are equipped with superior resources and better information than individual investors. Hence, if there is mispricing, we should, on average, expect institutional investors to exploit it, rather than individual investors. There is evidence to support this conjecture: Grinblatt, Titman, and Wermers (1997), Wermers (1999), Nofsinger and Sias (1999), and Grinblatt and Keloharju (2000) find that stock holdings of institutional investors earn positive abnormal returns, Dennis and Weston (2001) and Sias, Starks, and Titman (2001) provide evidence for information-based trading by institutional investors. Following this line of reasoning the underreaction hypothesis predicts that undervalued winners should experience a persistent increase in institutional investor holdings, while losers should exhibit persistent decreases. Again, the delayed overreaction hypothesis predicts the opposite. I test these predictions by examining the changes in institutional holdings up to five years after return shocks.

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6 To see why looking at long-run changes are important consider the finding in Chen, Hong, and Stein (2001) that there is a strong positive contemporaneous relation between returns and changes in breadth of mutual fund ownership. This result is consistent with underreaction, but it does not rule out alternative stories. Suppose there really is delayed overreaction: in this case breadth of ownership for winners could perhaps decrease some time after the return shock, reversing the contemporaneous increase. This could happen, for example, if many mutual fund managers follow momentum strategies, taking temporary long positions in temporarily overvalued stocks, which are eliminated before correction of this overvaluation sets in. Since explaining momentum is not the focus of their paper, CHS do not address this issue.

7 Cohen, Gompers, and Vuolteenaho (2001) run firm-level VARs and find that there is a positive relation between returns, and in particular the cash-flow-news-induced component of returns, and future institutional holdings. However, due to the structure imposed by the VAR there could be reversals of these changes at longer horizons that remain undetected. Furthermore, it would also be interesting to know the relationship to changes in breadth. Both issues are considered in this paper.
Since deviations from fundamental value are not directly observable, all three sets of tests employ indirect measures of mispricing. Consequently, each test suffers from a joint hypothesis problem. Inference in long-horizon returns tests depends on the assumption that the employed benchmark for expected return is correct. The tests using breadth of ownership assume that the CHS differences in opinion and short-sales constraints model holds, and the interpretation of results on the share of institutional holdings is based on the assumption that institutions trade smarter than individual investors. These joint hypotheses problems highlight the usefulness of considering several test that involve different assumptions, as done in this paper.

I also note that the tests conducted here may have power to reject the behavioral hypotheses, but they are not designed to discriminate between rational and behavioral theories of momentum. While mispricing theories have some implications for institutional investor behavior, it is not clear how institutional investors would react to the changes in risk that give rise to momentum in models like Berk, Green, and Naik (1999) and Johnson (2002).

**B. Basic data: US sample**

Data on US stock returns and market capitalizations are taken from the Center for Research in Security Prices (CRSP) monthly NYSE/AMEX/NASDAQ stock return files from January 1965 to December 2000. I eliminate closed-end funds, real estate investment trusts (REIT), American Depository Receipts (ADR), foreign companies, primes and scores. To correct for delisting bias I use the adjustment proposed in Shumway (1997) when the delisting return is missing on CRSP. Book value of equity is taken from the merged CRSP/COMPUSTAT database, and it is defined as common equity plus balance sheet deferred taxes. I calculate the book-to-market ratio $BM_t$ as book value of equity from the most recent fiscal year end that is preceding month $t$ by at least six months, divided by the market value of equity at the end of month $t$. The market value in the denominator is updated each month in order to capture the large swings experienced by extreme winners and losers in a timely fashion.

$LOGSZ_t$ is the log of end of month market capitalization. I also compute the average of the last six months monthly turnover, where monthly turnover is defined as monthly trading volume
divided by shares outstanding. To make turnover on NYSE/AMEX comparable with NASDAQ
turnover I normalize each firm’s turnover by the mean for its exchange (NYSE/AMEX or NASDAQ)
for the corresponding time period, by dividing it by this mean and subtracting one. This exchange-
adjusted turnover is denoted ADJTURNt.

Consistent with Fama and French (1993) I exclude firms with negative book values. I also
follow Jegadeesh and Titman (2001) and exclude stocks which are priced lower than $5. This is to
ensure that none of the results are driven by microstructure problems associated with very low priced
stocks. Both criteria are applied at the time of portfolio formation, i.e. at the end of month t.

C. Basic data: UK sample

Whenever feasible, I also use data from the UK to provide additional robustness checks.
However, I do not have extensive volume and ownership data for UK stocks, so its use is limited. All
listed UK firms for the sample period are identified from the master index of the London Share Price
Database (LSPD). Accounting information for these firms is taken from the Nagel (2001) data set,
which is free of survivorship bias and covers virtually all firms that have been listed on the London
Stock Exchange from 1955-1999. Stock returns and market capitalizations are obtained from the
LSPD. The LSPD has returns for all equities since 1975 and a fully representative one-in-three
stratified random sample from 1955 to 1974. I exclude investment trusts (closed-end funds) and
foreign stocks. When a stock delists and the delisting event reported in the LSPD suggests that the
stock delisted valueless, I assume a return of -100% at the date of delisting to avoid delisting bias.
Book value of equity is defined as ordinary share capital plus reserves plus deferred and future
taxation. BMt and LOGSZt are defined as in the US sample. Firms with negative book values are

8 It includes information from Datastream and the Cambridge/DTI database (see Meeks, Wheeler, and
Whittington, 1998, 1999), supplemented with handcollected balance sheets for all firms not covered in these two
sources. In terms of historical and cross-sectional coverage this merged data set of accounting information and
stock returns constitutes the largest of its kind outside of the US that I am aware of. See Nagel (2001) for more
details on this data. Dimson, Nagel, and Quigley (2001) report that in this sample the cross-section of stock
returns exhibits similar effects as in the US, in particular a strong return premium for high book-to-market
stocks.

9 See e.g. Dimson and Marsh (1983) for more details on the LSPD.
excluded. In the UK sample I exclude low priced stocks with a 30 pence cutoff at the time of portfolio formation. This excludes roughly the same proportion of firms as in the US sample.

D. Mutual fund stock holdings

Data on US mutual fund holdings are taken from the CDA/Spectrum Mutual Funds Holdings Database (maintained by Thomson Financial). I obtain quarterly stock holdings from the first quarter of 1980 to the end of 2000. SEC regulation N30-D requires mutual funds to file their stock holdings semi-annually. Thomson Financial collects this data and supplements it with information from voluntary quarterly reports. A very detailed overview of this database is given in Wermers (1999). The reporting dates vary across mutual funds, depending on their fiscal year ends, and not all of them are at the end of quarters. To be able to aggregate data across funds, I align all reports at the end of each quarter.

In each quarter \( t \), I compute the change in breadth of mutual fund ownership \( \Delta \text{BREADTH}_{\text{MUT}} \) like Chen, Hong, and Stein (2001) as the number of funds holding a stock in quarter \( t \), minus the number of funds holding the stock in quarter \( t-1 \), divided by the total number of funds in the universe at \( t-1 \). To eliminate effects of changes in the overall mutual fund sample, the universe of funds is kept constant from \( t-1 \) to \( t \). When no report is available, I assume that holdings remain unchanged\(^{10}\). For each stock I also calculate the change in the share of outstanding equity held by mutual funds \( \Delta \text{HOLD}_{\text{MUT}} \).

E. Institutional stock holdings

Data on institutional holdings are obtained from the CDA/Spectrum Institutional Holdings (13F) database (maintained by Thomson Financial). Since 1978 all institutions with more than $100 million under discretionary management are required to disclose their holdings to the SEC each quarter on form 13F. This concerns all common stock positions greater than 10,000 shares or $200,000, over which the manager exercises sole or shared investment discretion. The data is

\(^{10}\) Wermers (1999) finds that more than 80% of the funds in this database report quarterly, and virtually all funds report at least semi-annually.
aggregated at the institutional level. For example, in contrast to the above mutual funds data set, here
the holdings of mutual fund managers are not broken down into different funds; there are only
aggregated holdings for the whole company. Each institution is classified into five categories: (1)
banks, which mainly refers to holdings of banks’ trust departments, (2) insurance companies, (3)
investment companies, (4) investment advisors, and (5) others. The latter category includes pension
funds and university endowments; the investment advisors category includes investment banks,
brokerage firms, and also hedge funds. Summary statistics and more details about this database can be
found in Gompers and Metrick (2001).

I obtain quarterly holdings from this database starting in the first quarter of 1980, and ending
in the last quarter of 2000. I calculate the share of institutional ownership by summing the stock
holdings of all reporting institutions for each stock in each quarter. Stocks that are on CRSP, but
without any reported institutional holdings, are assumed to have zero institutional ownership. Since
very small institutions and holdings are not represented in the Spectrum database, ownership levels
may be understated to some extent. Gompers and Metrick (2001) conclude that this is unlikely to have
an important impact. By taking the difference of the share of institutional ownership from one quarter
to the next I compute its change $\Delta^{\text{HOLD}_{\text{INST}}}$.

I also use this data to compute an alternative measure of breadth of ownership, $\Delta^{\text{BREADTH}_{\text{INST}}}$, which is based on the entire universe of institutions, not just mutual funds. The
calculation is made in similar fashion as in the previous subsection, with the entity “institution”
replacing the entity “mutual fund”. This measure differs from $\Delta^{\text{BREADTH}_{\text{MUT}}}$ not only in covering a
larger set of investors, but also in that observations are aggregated at the company level. Hence,
$\text{BREADTH}_{\text{INST}}$ only changes if all portfolios held by the institution entirely get in or out into a stock.
In the more disaggregated mutual fund data it would change when one fund within a company’s
mutual fund family gets in or out.
F. Portfolio formation

In both US and UK samples I look at six-month momentum. At the end of each month $t$ all eligible stocks are ranked by their return over the past six months $MOM_6_t$ (month $t-5$ to $t$) and placed into five portfolios based on quintile breakpoints. Stocks are held in these portfolios for 5 years and returns are equally weighted. The proceeds from a stock that delists during the holding period are equally distributed among the other stocks in the portfolio. Summing these monthly portfolio returns yields cumulative returns, which are then averaged in event time. I only form portfolios if a full five year holding period is available. Hence, the last portfolio is formed at the end of December 1995.\footnote{This is to ensure that patterns in cumulative returns over the five holding years are not driven by time-variation in momentum profits. For example, if momentum were substantially above average for the portfolio formed at the end of 1999, including this portfolio would increase the average cumulative return for the first twelve event months, but not for later holding months, because the sample ends in December 2000.} Subtracting the return of the bottom past return quintile portfolio (“losers”) from the top return quintile portfolio (“winners”) yields a zero-investment momentum portfolio $WML$.

For abnormal return measurement purposes I form 25 size and book-to-market matching portfolios. Stocks are ranked by their $BM_t$ and market capitalization at the end of each month, and sorted independently into five size and five book-to-market groups based on quintile breakpoints. Portfolios are rebalanced each month, and returns are equally weighted. In the US, breakpoints are based on the NYSE sample. Similarly, 25 book-to-market and turnover portfolios are formed following the same procedure by sorting on $BM_t$ and $ADJTURN_t$, with $ADJTURN_t$, breakpoints based on the full sample.

G. Abnormal return metrics

To measure abnormal holding period returns of momentum portfolios I use characteristics adjusted returns. Each month $t$ every stock is matched to the benchmark portfolio corresponding to its time $t-1$ size and book-to-market, or, alternatively, book-to-market and volume. Subtracting the return of the matching portfolio from the individual stock return yields the abnormal return.

I also consider multifactor-adjusted returns. Grundy and Martin (2001) report that factor loadings of stocks with large positive or negative past returns are very different before and after these
return shocks. The factor-adjustment that I use accounts for this change in factor loadings by estimating loadings only from return observations after the return shock. Consider the winner minus loser WML portfolio formed at the end of each month \( t \), which is held for five years. Starting in holding month 13, I estimate the dynamic factor exposure of this portfolio with rolling 12-month window regressions, using the Fama and French (1993) three-factor model

\[
R_t = \alpha + b_{M,t} R_{M,t} + s_{SMB,t} R_{SMB,t} + h_{HML,t} R_{HML,t} + e_t
\]  
(1)

The regression is run over the window \( t+k-12 \) to \( t+k-1 \). The factor-adjusted return on WML in month \( t+k \) is then given by

\[
R_{t+k}^* = R_{t+k} - b_{M,t+k} R_{M,t+k} - s_{SMB,t+k} R_{SMB,t+k} - h_{HML,t+k}
\]  
(2)

This procedure is then repeated in \( t+k+1 \), \( t+k+2 \), etc. For the first 12 months of the holding period I use the factor loadings estimated from \( t+1 \) to \( t+12 \).

H. Summary statistics

Table I presents summary statistics for the variables used in this study. The first column shows results for the full sample, the other columns break down the sample into top, bottom, and middle quintiles by past return (MOM6\( t-1 \)) and lagged size (LOGSZ\( t-1 \)). In Panel A several points are noteworthy. First, the past return quintile statistics show that winners and losers differ with respect to BM and ADJTURN—characteristics known to predict future returns (Fama and French 1992; Datar, Naik, and Radeliffe 1998). Winners are tilted towards low BM and high ADJTURN, i.e. low expected return, or “growth” characteristics, whereas losers are tilted towards “value” characteristics. The implications of these differences in characteristics for drawing inferences from long-horizon returns of momentum strategies are explored in section II below. Second, all institutional ownership variables display by far the highest variation within the large firm quintile. This is a consequence of the fact that

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12 An alternative would be to form calendar time portfolios of winner and loser stocks in the first, second,..., fifth year after portfolio formation and regress the resulting five return time-series on the Fama-French factors as in Jegadeesh and Titman (2001). However, the factor exposure of past return sorted portfolios is related to factor realizations during the formation period. For example, in up-markets the winner portfolio is tilted towards high beta stocks, and the loser portfolio towards low beta stocks. If there is negative autocorrelation in the market factor, this could, quite mechanically, result in reversals, as high beta stocks, i.e. winners, will then underperform in the future relative to low beta losers. The calendar time method keeps loadings constant and hence does not capture this time-variation in factor loadings.
the share of institutional ownership is much higher for large firms. In designing my tests I need to be careful to take into account this cross-sectional heterogeneity. The summary statistics for winner and loser quintiles also indicate that both BREADTH and HOLD tend to increase (decrease) after large positive (negative) returns. This is consistent with the findings of Chen, Hong, and Stein (2001) and Cohen, Gompers, and Vuolteenaho (2001). Section III investigates what happens to BREADTH and HOLD in the long-run, and how this relates to the possible sources of momentum profits.

II. Long-horizon Returns

In this section I explore the evidence on long-horizon returns of momentum strategies. Figure 1a depicts the average cumulative returns of a winner minus loser zero-investment strategy when portfolios are formed monthly and held for five years. The bold parts of the lines indicate where cumulative returns are significantly different from zero at a 5% level, based on Newey-West (1987) autocorrelation-consistent standard errors. As the figure shows, momentum profits revert after a holding period of about twelve months. And they do so even stronger in the UK. This confirms the basic finding of Jegadeesh and Titman (2001). Taken at face value, these reversals seem to contradict the underreaction explanation of momentum, as momentum profits appear entirely transitory. However, a well-known problem in evaluating long-horizon returns is their sensitivity to the chosen benchmark for expected returns. Hence, these reversals might not be a correction of previous mispricing—as suggested by delayed overreaction theories—but instead a manifestation of winners being less risky or more liquid than losers. The latter possibility is underscored by the fact that “correction” seems to take unduly long. As noted by Jegadeesh and Titman (2001), and confirmed here for the UK (not shown), the reversals even continue beyond the five year holding period.

A. Benchmark sensitivity of reversals in momentum payoffs

In light of the summary statistics shown in table I the reversals in momentum profits in figure 1a are perhaps not too surprising: recall that winners become low BM, and high ADJTURN, stocks, while losers experience the opposite. Hence, once the initial momentum effect dies out after about 12
holding months, winners have characteristics known to be associated with low future returns (Fama and French 1992; Datar, Naik, and Radeliffe 1998), and hence underperform losers, giving rise to the reversals in winner minus loser cumulative returns.

Nevertheless, Jegadeesh and Titman (2001) report that the reversals are not fully explained by the Fama-French (1993) three-factor model in calendar time portfolio regressions. In contrast, figure 1b shows that reversals largely disappear when the return of a matched size- and book-to-market portfolio is subtracted from individual stock’s returns before computing portfolio returns. Hence, whether momentum profits revert or not appears to be sensitive to the choice of the benchmark for expected returns.

Table II presents some further evidence using a variety of different benchmarks. The table shows the cumulative abnormal return within the first, second,….., fifth year after portfolio formation, as well as the cumulative abnormal return over years 2 to 5. The first row in panel A shows that the reversals in year 2 to 5 in unadjusted returns are statistically significant. The cumulative return over year 2 to 5 is –6.44% (t-stat. -2.17). When returns are adjusted for dynamic exposure to the three Fama-French factors in the second row of this table, reversals become insignificant. With the adjustment method used here the factor model does a better job in explaining reversals than the calendar time regressions in Jegadeesh and Titman (2001). In their paper the average monthly three-factor alpha in years 2-5 is –0.14% (t-stat. –3.26), which corresponds to roughly -8% cumulative alpha over years 2 to 5. In comparison, the abnormal return here is –2.50%. (t-stat. –0.88).  

The table also shows that there are no significant abnormal returns over years 2 to 5 when firms are matched to corresponding size and book-to-market, or book-to-market and volume portfolios. Panel B performs similar tests with the UK sample. Here, reversals in raw returns are much stronger than in the US. Adjusting for size and book-to-market eliminates the bulk of the reversals, but there is still some significant abnormal return left.

I also look at winners and losers separately to check whether there is some asymmetry in long-run returns. Table II shows that book-to-market and volume adjusted returns for winners and losers in years 2 to 5 are very similar. Interestingly, in contrast to Hong, Lim, and Stein (2001), I do not find a

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13 Note however that Jegadeesh and Titman (2001) use decile, not quintile portfolios.
strong asymmetry between winners and losers in the first holding year. In the US the initial momentum of winners and losers is of similar magnitude, and in both cases there are no significant reversals. If anything, there may be some asymmetry in the UK. The lack of consistent asymmetry here shows that their result is perhaps not very robust to methodological changes. In their paper they do not control for book-to-market or volume, and they form three past return portfolios, not five. I note however, that there is one feature of the results that fits their story. In the US and the UK the drift for losers appears to last longer, both for volume and book-to-market as well as size and book-to-market adjusted returns (not shown). The sign of the second year abnormal return is consistently of the same sign at the first year abnormal return. This squares well with their argument that short-sales constraints slow down the incorporation of negative information into prices.

B. Trading volume and reversals in momentum payoffs

There is another result in the recent literature that appears to support the delayed overreaction explanation. One of the findings in Lee and Swaminathan (2000) is that trading volume (measured as turnover) helps to predict whether momentum profits revert or persist. They propose a “momentum-life-cycle” model in which volume—in addition to its known role as a predictor in the cross-section of returns—interacts in such a way with the momentum effect that high volume winners are near their valuation peak and face reversals, whereas low volume winners, close to their “valuation through”, have high and persistent momentum profits. In contrast, for losers high volume indicates persistence, and low volume predicts reversals.

They form two strategies. One, dubbed “early”, is long low volume winners and short high volume losers. The other one, “late”, is long high volume winners and short low volume losers. Table III examines their findings. Momentum and volume portfolios are defined by quintile breakpoints.14 Turnover is measured by exchange adjusted turnover ADJTURN, over a period of six months. Panel A confirms their result: "early" strategy momentum profits persist, whereas "late" strategy profits revert

14The methodology here is slightly different. Lee and Swaminathan use averages of daily instead of monthly turnover, they intersect three volume and ten past return portfolios, not five and five; they report buy and hold returns instead of cumulative returns, and they use NYSE/AMEX stocks only. However, the results in unadjusted returns are essentially the same.
and quickly turn negative. Lee and Swaminathan argue that this supports their “momentum-life-cycle” model, which is essentially very similar to delayed overreaction theories.

However, does this result really imply that there is any interaction between trading volume and momentum? Or, said slightly differently: does this result show anything else than that there is (a) momentum and (b) a return premium associated with low turnover like in Datar, Naik, and Radcliffe (1998)? After all, “early” is a high volume minus low volume strategy, and “late” is a low volume minus high volume strategy. Hence, the seemingly persistent (reverting) profits of the early (late) strategy might just reflect the fact that these strategies are not volume-neutral, and not some interaction of volume with momentum. Furthermore, as Lee and Swaminathan point out, turnover is also negatively correlated with book-to-market. “Early” is therefore tilted towards being long in value stocks and “late” towards growth stocks. This explains why in panel B, after adjusting returns for size and book-to-market, the bulk of the effect goes away and year 2 to 5 cumulative returns are insignificant. In panel C I check whether the remaining effect reflects a low volume premium, irrespective of momentum, or whether it is due to interaction of volume and momentum. I adjust returns for book-to-market and volume. Sorting on past returns and volume and then adjusting for volume may seem tautological—and it may be so indeed, but only if there is no interaction of volume and momentum. Hence, in panel C I ask whether high volume winners differ from low volume winners (or high volume losers from low volume losers) in any other way than the typical high volume stock from the typical low volume stock. The results show that they do not. After this adjustment cumulative returns for the two strategies are very similar, and momentum profits persist for both. The different long-horizon returns of unadjusted early and late strategies in panel A are therefore merely a restatement of the fact that book-to-market and trading volume are characteristics related to future returns, but there is no evidence of any interaction of these characteristics with momentum that would provide further insights into the causes of momentum effects.15

15 Another example may help to illustrate this point. One can easily construct a very “persistent” momentum strategy similar to the above “early” strategy by going long high book-to-market-winners and shorting low book-to-market-losers. However, this “persistence” does not reveal anything about the source momentum effect. The strategy is simply an overlay of a high book-to-market minus low book-to-market and a winners minus losers strategy.
In summary, the evidence on long-horizon returns of momentum strategies does not provide a compelling case for delayed overreaction. After adjusting for characteristics known to be related to future returns, and book-to-market in particular, momentum profits do not exhibit reversals anymore. An intersection of past return and volume sorts does not provide any further insights. If these characteristics capture rational expected returns, then the findings in this paper suggest that momentum is caused by underreaction—or by any other mechanism that causes continuations in returns—but not by delayed overreaction. In fact, the notion that stocks which have experienced large positive shocks to returns become less risky (reflected in lower book-to-market) and more liquid (reflected in higher trading volume) than stocks that have experienced large negative shocks seems intuitive. However, volume and book-to-market characteristics might also pick up some overreaction-induced mispricing. In this case the characteristics-adjustment of returns could eliminate the contribution of delayed overreaction to long-run reversals. The source of return premia associated with firm characteristics such as book-to-market is still subject of an ongoing debate and cannot be resolved here. At the least however, the results in this section raise the possibility that momentum is caused by underreaction—despite reversals of momentum profits in unadjusted returns. In the remainder of the paper I examine whether the trading behavior of institutional investors can provide further insights that allow to discriminate between delayed overreaction and underreaction explanations of momentum.

III. Momentum and Institutional Ownership

In this section I use changes in breadth of ownership and changes in the share of institutional holdings as valuation indicators, where decreases in these variables indicate overvaluation, and increases indicate undervaluation. The Chen, Hong, and Stein (2001) model provides the theoretical rationale for the role of breadth as a valuation indicator. Of course, there may be alternative explanations for why winners and losers might experience changes in breadth of ownership—possibly unrelated to the effects described by CHS. I discuss those subsequently in section IV.

16 Fama and French (1993) argue that the small size and high book-to-market return premia are compensation for risk. Datar, Naik, and Radcliffe (1998) propose that the low volume return premium is compensation for illiquidity.
17 See e.g. Daniel, Hirshleifer, and Subrahmanyam (2001) and Vassalou (2001) for recent contributions to this debate.
A. Changes in breadth of ownership

Figure 2 depicts changes in breadth of mutual fund ownership $\Delta$BREADTH$_{\text{MUT}}$ for winner and loser portfolios. Starting in July 1980 stocks are sorted each month into quintile portfolios by past returns and held for five years. I calculate the average change in breadth of ownership for each portfolio by taking the equal-weighted average of each stock’s $\Delta$BREADTH$_{\text{MUT}}$. These numbers are then averaged in event time. The reporting frequency for mutual fund holdings is usually quarterly, but in a few cases it can also be semi-annually, or annually. Hence, at monthly frequency $\Delta$BREADTH$_{\text{MUT}}$ is autocorrelated. For this reason standard errors are based on Newey-West (1987) with 11 lags. Bold parts of the lines in indicate where the mean $\Delta$BREADTH$_{\text{MUT}}$ is significantly different from zero at a 5% level. To eliminate any effect of time trends in $\Delta$BREADTH$_{\text{MUT}}$ for a typical stock over the sample period, I subtract $\Delta$BREADTH$_{\text{MUT}}$ of the middle past return quintile portfolio from $\Delta$BREADTH$_{\text{MUT}}$ of winners and losers.

Figure 2 shows that breadth of ownership of winners increases during the first year after portfolio formation. In first quarter following their large return, winners gain close to 0.04% of the universe of mutual funds as new investors (net of lost investors). Losers experience a loss in similar size. Given that the average stock in this sample is only held by 0.80% of existing funds, these changes indicate a considerable reshuffling of the ownership structure of winners and losers—in particular if one considers the fact that some of these funds explicitly or implicitly follow indexing strategies, which constrains their ability to trade actively in and out of stocks. Most importantly, there is no indication of any significant reversals during later years. When a stock experiences a large positive (negative) return shock more (less) mutual funds hold it afterwards, and this change in breadth of ownership is very persistent.

I examine the relation between past returns and future changes in $\Delta$BREADTH$_{\text{MUT}}$ more formally in table IV by running cross-sectional Fama-MacBeth regressions. The dependent variable in these regressions is $\Delta$BREADTH$_{\text{MUT}}$, averaged over four quarters $t-3$ to $t$. Since the variation in $\Delta$BREADTH$_{\text{MUT}}$ is much higher among large stocks (see table I), I follow CHS and run these cross-sectional regressions separately within size quintile groups. Estimated coefficients are then averaged.
first across size groups within each cross-section, and then across time. Standard errors are obtained from the time-series variation of coefficient estimates in the usual Fama-MacBeth (1973) fashion.

In panel A $\Delta$BREADTH\textsubscript{MUT} is regressed on past six months returns MOM\textsubscript{6-t}. The different columns report results for various lags $k$ (in quarters) of this variable. The coefficient in the first column confirms the positive contemporaneous relationship between $\Delta$BREADTH\textsubscript{MUT} and MOM\textsubscript{6} documented by CHS. The second column shows that a return shock also results in a significant change in breadth in the same direction over the first four quarters following the shock. At longer lags $k$ the estimates are insignificant, and there is no indication of any substantial reversals. Hence, the cross-sectional regressions confirm the inference drawn from figure 2. In panel B the regression specification includes several control variables to check the robustness of the momentum-breadth relationship. First, changes in breadth of ownership in response to large return realizations might be driven simply by changes in the overall share of mutual fund holdings in a given stock—for example, because shares move from mutual funds to individual investors. In this case BREADTH\textsubscript{MUT} may go down even though breadth of ownership within a more broadly defined set of investors may have remained unchanged. To control for this, I include the contemporaneous time $t$ change in the share of outstanding equity held by mutual funds $\Delta$HOLD\textsubscript{MUT}. With this control in place, the coefficient on $\Delta$BREADTH\textsubscript{MUT} reflects only reallocations within the mutual fund sector. Second, there is a possibility that large returns lead to changes in firm characteristics and that these in turn drive the observed changes in future breadth, perhaps because mutual fund managers have a preference for stocks with certain characteristics. For this reason, I control for LOGSZ, BM, and ADJTURN at the time just before the measured change in breadth occurs, i.e. at $t-4$. The results show that after controlling for these variables the average $R^2$ is much higher, yet the relationship between past returns and BREADTH\textsubscript{MUT} is unchanged at all horizons $k$.

Panel C reports the results of a further robustness check. I replicate the panel B regressions with $\Delta$BREADTH\textsubscript{INST}, which is the change in breadth among all institutional investors, not just mutual funds. During the sample period considered here, mutual funds, on average, only hold less than 3% of

\footnote{Gompers and Metrick (2001) for example find that institutional investors prefer large and more liquid stocks.}
aggregate outstanding equity. Institutional investors hold seven times this amount, so this is an interesting extension. ∆BREADTH\textsubscript{INST} and ∆BREADTH\textsubscript{MUT} are positively correlated, but not perfectly so (correlation coefficient = 0.54). The results indicate that the positive relationship between past returns and breadth also holds for ∆BREADTH\textsubscript{INST} at all horizons \(k\). Hence, the original CHS breadth of mutual fund ownership variable appears to capture an effect that is not restricted to the universe of mutual funds. In the remainder of the paper I focus on the broader ∆BREADTH\textsubscript{INST} variable.

**B. Changes in the share of institutional holdings**

Figure 3 shows the changes in the average share of institutional holdings ∆HOLD\textsubscript{INST} experienced by winners and losers. During the first year after portfolio formation stocks in the winner quintile attract higher institutional holdings, whereas ∆HOLD\textsubscript{INST} for losers is negative. Moreover, these changes in the share of institutional holdings do not appear to revert during the five years after the return shock.

Table V presents the results of cross-sectional regressions similar to those in table IV, with ∆HOLD\textsubscript{INST} as the dependent variable. Panel A shows that there is a positive contemporaneous and one year lagged relationship between ∆HOLD\textsubscript{INST} and MOM\textsubscript{6}, consistent with the results in Cohen, Gompers, and Vuolteenaho (2001). After the first year however there are some significant reversals. Nevertheless, the cumulative effect is still positive even after 16 quarters. Interestingly, panel B shows that once changes in breadth of ownership and firm characteristics are controlled for, the relationship between MOM\textsubscript{6} and future ∆HOLD\textsubscript{INST} is negative already at a lag of four quarters. Hence, holding the breadth of ownership and everything else constant, institutional holdings tend to go down after a positive return shock.

The following simple analysis illustrates this point. Let \(h_t^*\) denote the average share held by the institutions invested in a stock, and \(f_t\) be the total number of institutional investors that exist at time \(t\). Then BREADTH \((h_t)\) and the share of institutional holdings \((h_t)\) are related through the identity \(h_t = b_t f_t h_t^*\). Some simple manipulation shows that the change in breadth \(\Delta b_t = b_t - b_{t-1}\) and the change in the share of institutional holdings \(\Delta h_t = h_t - h_{t-1}\) are related through

21
\[ \Delta h_t = (\Delta b_t \Delta h_t^* + \Delta b_t \Delta h_t^* + b_{t-1} \Delta h_t^*) f_t \]  

(3)

The results in table V show that if \( \Delta b_t \) is zero, then \( \Delta h_t \) is negative. Hence, what apparently happens is that in response to a positive return shock the average holding per institution \( h_t^* \) in a given stock declines, while the percentage of institutions with a non-zero holding \( b_t \) increases sufficiently to raise the aggregate share of institutional holdings in this stock \( h_t \) above pre-shock levels. The increase in the share of institutional holdings in the first year after a positive return shock is therefore driven by an increase in breadth, but not in average holdings.

IV. Discussion

The motivation for the tests in the previous section is the CHS model, based on differences in opinion and short-sales constraints. The evidence indicates that winners (losers) experience a very persistent increase (decrease) in breadth of ownership. In the context of the CHS model this fits naturally with underreaction theories of momentum: winners are underpriced, which prompts pessimists—previously sitting on the sidelines—to buy the stock, resulting in higher breadth. Losers, in contrast, are overpriced and hence some investors with less optimistic valuations sell. Of course, there are also other potential explanations for the patterns in institutional trading uncovered in this paper. Some nonetheless support the underreaction story. One alternative explanation, for example, would be some stock-picking skill on the part of institutional investors. If so, the increase (decrease) in breadth for winners (losers) again implies that winners are undervalued and losers overvalued which supports the underreaction explanation of stock return momentum. But there are some other possible stories that could be more supportive of delayed overreaction.

A. Attention and neglect

Possibly, large positive returns could raise the attention devoted to a stock, thereby contributing to increased breadth even though such winner stocks are overpriced. In some of their tests, CHS decompose changes in breadth as \( \Delta \text{BREADTH}_t = \text{IN}_t - \text{OUT}_t \), that is, into the percentage...
of managers establishing a new long position in this stock at time $t$ (IN), and the percentage of those eliminating their positions (OUT). This decomposition is also useful for the purposes of this paper.

Table VI repeats the regressions of table IV panel C, this time with IN$_t$ and OUT$_t$ as dependent variables instead of $\Delta$BREADTH$_{INST,t}$. To investigate the effect separately for winners and losers I break-up MOM6 into MOM6$^+$, which is set to zero when MOM6$_t$ is below the average MOM6$_t$ in the time $t$ cross-section, and MOM6$^-$, which is set to zero when MOM6$_t$ is above the average MOM6$_t$. The regressions are run with the same set of control variables as before. To reduce clutter, I do not report their coefficients.

A comparison of the coefficients on MOM6$^+$ and MOM6$^-$ shows that past negative returns lead to an increase in future OUT, but not so much action in IN. In contrast, positive past returns are associated with higher future IN, but they do not have much impact on future OUT. The fact that losers experience an increase in future OUT cannot be explained by the increased attention story. After all, these loser stocks should already be in the “attention set” of those investors who sell them. Yet the results are consistent with differences in opinion, short-sales constraints, and underreaction. With underreaction, a positive return shock leads to undervaluation. The investors already holding the stock have no new reason to sell the stock, but a certain number of pessimist are now willing to hold the stock, leading to an increase in IN. Similarly, underreaction results in overvaluation of losers. The pessimists already sitting on the sidelines have no reason to enter a new long position, but a certain number of optimists will now sell their holdings, resulting in an increase in OUT.

**B. Momentum style investing**

Some institutional investors might follow mechanical momentum strategies or “styles”. If the number of such momentum following institutions is sufficiently large, this too could give rise to increases in breadth after positive return shocks as observed above. If so, then changes in breadth should recurrently be driven by trades of the same subset of investors. In contrast, in the CHS model breadth is determined by dispersion in opinion concerning the valuation of a particular stock. Those investors, who are optimists for a certain stock today need not be among the optimists for another stock today or tomorrow—they could as well be among the pessimists in other circumstances.
To check the effect of momentum style investing, I classify investors based on their previous trading history. Each quarter I form momentum quintiles and assign a “momentum index” from –2 to +2 to each quintile from losers to winners. When an institution establishes a new position in a certain stock I note the stock’s momentum index. Based on all new positions established within a quarter I compute the average IN-momentum index for each institution. When an institution did not establish a new position at all the IN-momentum index is set to zero. In quarter $t$ an institution is classified as IN-momentum investor, if its average IN-momentum index over the quarters $t-1$ to $t-4$ is above the 70th percentile in this cross-section, i.e. when its buys were concentrated among winners in the recent past. I run a similar classification for OUT-trades, that is, for eliminations of existing positions. An institution is classified as OUT-momentum investor, if its average OUT-momentum index over the last four quarters is below the 30th percentile. I then compute $XIN_t$ and $XOUT_t$ in the same way as $IN_t$ and $OUT_t$ in the previous subsection, with the difference that now $XIN_t$ excludes the trades of IN-momentum investors, and $XOUT_t$ excludes the trades of OUT-momentum investors. By doing this I aim to eliminate the effect of mechanical momentum style investing on changes in breadth of ownership.

The evidence in table VII shows that excluding momentum investors weakens the relationships between past returns and future IN and OUT. However, the basic results are still intact. Even after excluding the trades of investors who follow momentum styles, there is still evidence that breadth of ownership increases after positive return shocks, driven by IN, and decreases after negative return shocks, driven by OUT. Some of the changes in breadth apparently reflect mechanical momentum trading rather than the effect proposed by CHS. But after accounting for this, the results still hold. This gives further support to the underreaction hypothesis.

C. Unsuccessful stock-picking

A further alternative explanation would be that there really is delayed overreaction, but many institutional investors tend to discard losers and invest and hold on to winners, in spite of their excessive valuation, perhaps because they prefer to hold more “glamorous” stocks. In other words, changes in breadth of ownership could reflect detrimental stock-picking activity of institutional
investors. This possibility cannot entirely be ruled out, but I find it unconvincing for several reasons. First, there is a large literature showing that institutional investors are more informed and that they outperform to some extent. Grinblatt, Titman, and Wermers (1995) show that mutual funds have some stock selection ability that allows them to earn abnormal returns of a magnitude roughly equal to their expenses. Similarly, herding among institutional investors appears to speed price adjustment rather than destabilizing prices. Wermers (1999) examines herding among mutual funds and finds that stocks bought by herds tend to have higher returns in the following four quarters. Chen, Jegadeesh, and Wermers (2000) show that increases in mutual fund holdings forecast high returns over the next year. Nofsinger and Sias (1999) and Prinsky (2000) present similar evidence for other groups of institutional investors. Dennis and Weston (2001) provide microstructure evidence for informed trading by institutions. Sias, Starks, and Titman (2001) find that price pressure effects of institutional trading are driven by informational reasons. Furthermore, as the results in section III.B. show, the increase in breadth in the first year after portfolio formation also leads to an increase in the average share of winners’ outstanding equity held by institutional investors. To reconcile this finding with delayed overreaction would mean that those investors with superior resources and best access to information, systematically invest in overvalued stocks, and shun undervalued stocks. Even more puzzling, this would imply that individuals, the residual group of investors, trade at the expense of institutions. This would not be consistent with the evidence on trading behavior of individual investors reported in Barber and Odean (2000), and Grinblatt and Keloharju (2000), among others.

V. Conclusions

This paper shows that delayed overreaction is unlikely to be the source of momentum effects—in spite of the long-run reversals in momentum profits documented in prior research. First, the evidence for long-run reversals in momentum payoffs is very sensitive to the employed benchmark for expected returns. After adjusting returns for differences in characteristics between winners and losers, such as size, book-to-market, and trading volume, the reversals disappear, which makes the results consistent with underreaction theories. Second, large positive (negative) returns lead to a very
persistent increase (decrease) in breadth of institutional ownership. Driven by these changes in breadth of ownership, the aggregate share of institutional investor holdings also changes in the same direction. These changes in institutional ownership suggest that underreaction, not delayed overreaction is the most promising behavioral explanation of momentum. The evidence hence supports models like Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999), where momentum effects are mainly driven by underreaction—or other models that generate underreaction-type price patterns. The evidence is not consistent with delayed overreaction models like Daniel, Hirshleifer, and Subrahmanyam (1998).

The tests in this paper that use breadth of ownership as an indicator of misvaluation are motivated by the Chen, Hong, and Stein (2001) differences in opinion and short-sales constraints model. However, as shown, the conclusions drawn here also hold under some alternative explanations. In essence, a reconciliation of delayed overreaction momentum with the findings in this paper would require that there be a large number of institutions which systematically invest in overvalued stocks and sell undervalued stocks. At this point, given the existing evidence on trading performance of institutions and individuals, this does not appear plausible. However, future research may provide further insights into this interesting issue.
References


Chan, Wesley S.. 2001, Stock price reaction to news and no-news: drift and reversal after headlines, working paper, MIT.


Grinblatt, Mark, and Bing Han, 2001, The disposition effect and momentum, working paper, UCLA.


Hvidkjaer, Soeren, 2000, A trade-based analysis of momentum, working paper, University of Maryland.


Prinsky, Christo A., 2000, Are financial institutions better investors?, working paper, Ohio State University.


### Table I
**Summary statistics**

The US sample in panel A covers NYSE/AMEX/NASDAQ stocks from 1964 to 2000. The UK sample in panel B covers stocks on the London Stock Exchange from 1957 to 2000. US Institutional Ownership related variables are available from 1980 to 2000. MOM6t is the return over the last two quarters. LOGSZt is the log of market capitalization at the end of quarter t. BMt is the book-to-market ratio, where the market capitalization is measured at the end of quarter t. ADJTURNt is the average monthly turnover over the last two quarters, normalized by the average turnover for the firm’s exchange (NYSE/AMEX or NASDAQ) over the same two quarters. For institutional ownership variables the subscript MUT denotes the mutual funds sample, INST denotes the institutional investor (13F) sample. BREADTHt is the fraction of institutional investors holding the stock at the end of quarter t. ∆BREADTHt is the change in breadth of ownership from quarter t-1 to t. HOLDt is the share of outstanding shares held by institutional investors, and ∆HOLDt denotes its change over the last quarter. Size and momentum quintiles are formed based on quarter t-1 SZ and MOM6. US size breakpoints are based on the NYSE sample.

#### Panel A: US

<table>
<thead>
<tr>
<th>Variable</th>
<th>MOM6t, Quintiles</th>
<th>SZt, Quintiles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
<td>Losers</td>
</tr>
<tr>
<td>MOM6t</td>
<td>Mean</td>
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</tr>
<tr>
<td>%</td>
<td>Std.dev.</td>
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<td>LOGSZt</td>
<td>Mean</td>
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<tr>
<td>%</td>
<td>Std.dev.</td>
<td>2.09</td>
</tr>
<tr>
<td>BMt</td>
<td>Mean</td>
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</tr>
<tr>
<td>%</td>
<td>Std.dev.</td>
<td>1.82</td>
</tr>
<tr>
<td>ADJTURNt</td>
<td>Mean</td>
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</tr>
<tr>
<td>%</td>
<td>Std.dev.</td>
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</tr>
<tr>
<td>BREADTHMUT,t</td>
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<tr>
<td>%</td>
<td>Std.dev.</td>
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</tr>
<tr>
<td>BREADTHINST,t</td>
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<tr>
<td>%</td>
<td>Std.dev.</td>
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<td>∆BREADTHMUT,t</td>
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</tr>
<tr>
<td>%</td>
<td>Std.dev.</td>
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</tr>
<tr>
<td>∆BREADTHINST,t</td>
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<td>%</td>
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<td>HOLDMUT,t</td>
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<tr>
<td>%</td>
<td>Std.dev.</td>
<td>5.26</td>
</tr>
<tr>
<td>HOLDINST,t</td>
<td>Mean</td>
<td>21.39</td>
</tr>
<tr>
<td>%</td>
<td>Std.dev.</td>
<td>22.95</td>
</tr>
<tr>
<td>∆HOLDMUT,t</td>
<td>Mean</td>
<td>-0.03</td>
</tr>
<tr>
<td>%</td>
<td>Std.dev.</td>
<td>2.21</td>
</tr>
<tr>
<td>∆HOLDINST,t</td>
<td>Mean</td>
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</tr>
<tr>
<td>%</td>
<td>Std.dev.</td>
<td>5.62</td>
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</table>
### Panel B: UK

<table>
<thead>
<tr>
<th></th>
<th>MOM$_{6_t}$ Quintiles</th>
<th></th>
<th>SZ$_{t-1}$ Quintiles</th>
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<tbody>
<tr>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Full sample</td>
<td>Losers 2-4 Winners</td>
<td>Small 2-4 Large</td>
<td></td>
</tr>
<tr>
<td>MOM$_{6_t}$ %</td>
<td>Mean</td>
<td>-0.13 0.14 0.57</td>
<td>0.09 0.13 0.13</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Std.dev.</td>
<td>0.18 0.17 0.58</td>
<td>0.44 0.38 0.31</td>
<td></td>
</tr>
<tr>
<td>LOGSZ$_t$</td>
<td>Mean</td>
<td>9.04 9.33 9.06</td>
<td>7.26 9.37 11.85</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Std.dev.</td>
<td>2.49 2.50 2.49</td>
<td>1.77 1.73 2.07</td>
<td></td>
</tr>
<tr>
<td>BM$_t$</td>
<td>Mean</td>
<td>1.33 1.18 1.06</td>
<td>1.88 1.07 0.82</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Std.dev.</td>
<td>2.02 1.68 1.77</td>
<td>2.70 1.49 0.92</td>
<td></td>
</tr>
</tbody>
</table>
### Table II

**Characteristics- and three-factor-adjusted long-run returns of momentum strategies**

At the end of each month, stocks are ranked and sorted into quintiles by MOM6. Portfolios are formed of stocks in similar quintiles, their returns are equally weighted, and the portfolios are held for five years. A winner minus loser strategy (WML) is long the top quintile portfolio and short the bottom quintile portfolio. The resulting sequence of five-year WML return series is then averaged in event time. The table reports the cumulative event time returns within the first, second, ..., fifth, and second to fifth holding years. In the first row returns are unadjusted. In the second row returns are adjusted for dynamic exposure to the Fama-French factors. The remaining rows present size and book-to-market- and book-to-market and turnover-adjusted returns, based on a matching portfolio approach. The US sample in panel A comprises NYSE/AMEX/NASDAQ stocks from 1964 to 2000. The UK sample in panel B comprises London Stock Exchange stocks from 1957 to 2000. Returns are reported in percent. t-statistics, reported in parentheses, are based on autocorrelation- and heteroskedasticity consistent Newey-West standard errors with 11 lags (47 for the years 2-5 results).

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
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<th>4</th>
<th>5</th>
<th>2 - 5</th>
</tr>
</thead>
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<td><strong>Panel A: US</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WML - unadj.</td>
<td>8.08</td>
<td>-1.73</td>
<td>-1.15</td>
<td>-1.73</td>
<td>-1.84</td>
<td>-6.44</td>
</tr>
<tr>
<td></td>
<td>(6.13)</td>
<td>(-1.93)</td>
<td>(-1.03)</td>
<td>(-1.94)</td>
<td>(-1.68)</td>
<td>(-2.17)</td>
</tr>
<tr>
<td>WML - three-factor-adj.</td>
<td>11.26</td>
<td>-0.78</td>
<td>-0.08</td>
<td>-0.89</td>
<td>-0.92</td>
<td>-2.50</td>
</tr>
<tr>
<td></td>
<td>(7.82)</td>
<td>(-0.87)</td>
<td>(0.07)</td>
<td>(-0.80)</td>
<td>(-0.70)</td>
<td>(-0.88)</td>
</tr>
<tr>
<td>WML - SZ/BM-adj.</td>
<td>10.09</td>
<td>0.16</td>
<td>-0.18</td>
<td>-0.33</td>
<td>-0.17</td>
<td>-0.53</td>
</tr>
<tr>
<td></td>
<td>(9.07)</td>
<td>(0.24)</td>
<td>(-0.19)</td>
<td>(-0.33)</td>
<td>(-0.13)</td>
<td>(-0.19)</td>
</tr>
<tr>
<td>WML - BM/TURN-adj.</td>
<td>10.81</td>
<td>0.37</td>
<td>0.51</td>
<td>0.53</td>
<td>-0.12</td>
<td>1.28</td>
</tr>
<tr>
<td></td>
<td>(9.45)</td>
<td>(0.51)</td>
<td>(0.48)</td>
<td>(0.49)</td>
<td>(-0.09)</td>
<td>(0.37)</td>
</tr>
<tr>
<td>Winners - BM/TURN-adj.</td>
<td>5.17</td>
<td>-0.26</td>
<td>0.56</td>
<td>0.96</td>
<td>1.14</td>
<td>2.39</td>
</tr>
<tr>
<td></td>
<td>(8.14)</td>
<td>(-0.40)</td>
<td>(0.75)</td>
<td>(1.32)</td>
<td>(1.39)</td>
<td>(0.79)</td>
</tr>
<tr>
<td>Losers - BM/TURN-adj.</td>
<td>-5.64</td>
<td>-0.63</td>
<td>0.05</td>
<td>0.43</td>
<td>1.26</td>
<td>1.11</td>
</tr>
<tr>
<td></td>
<td>(-8.04)</td>
<td>(-1.51)</td>
<td>(0.09)</td>
<td>(0.74)</td>
<td>(1.63)</td>
<td>(0.95)</td>
</tr>
<tr>
<td><strong>Panel B: UK</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WML - unadj.</td>
<td>8.47</td>
<td>-2.36</td>
<td>-3.85</td>
<td>-3.72</td>
<td>-2.40</td>
<td>-12.33</td>
</tr>
<tr>
<td></td>
<td>(6.57)</td>
<td>(-2.86)</td>
<td>(-3.52)</td>
<td>(-4.18)</td>
<td>(-3.18)</td>
<td>(-7.53)</td>
</tr>
<tr>
<td>WML - three-factor-adj.</td>
<td>8.78</td>
<td>-1.53</td>
<td>-1.57</td>
<td>-2.85</td>
<td>-1.85</td>
<td>-7.81</td>
</tr>
<tr>
<td></td>
<td>(6.43)</td>
<td>(-1.56)</td>
<td>(-1.60)</td>
<td>(-3.02)</td>
<td>(-2.00)</td>
<td>(-3.99)</td>
</tr>
<tr>
<td>WML - SZ/BM-adj.</td>
<td>9.52</td>
<td>-0.84</td>
<td>-2.3</td>
<td>-1.81</td>
<td>-0.65</td>
<td>-5.6</td>
</tr>
<tr>
<td></td>
<td>(9.74)</td>
<td>(-1.42)</td>
<td>(-2.85)</td>
<td>(-2.06)</td>
<td>(-0.89)</td>
<td>(-2.36)</td>
</tr>
<tr>
<td>Winners - SZ/BM-adj.</td>
<td>3.92</td>
<td>-1.29</td>
<td>-2.01</td>
<td>-1.63</td>
<td>-0.97</td>
<td>-5.89</td>
</tr>
<tr>
<td></td>
<td>(8.83)</td>
<td>(-3.73)</td>
<td>(-4.43)</td>
<td>(-3.56)</td>
<td>(-2.38)</td>
<td>(-5.27)</td>
</tr>
<tr>
<td>Losers - SZ/BM-adj.</td>
<td>-5.6</td>
<td>-0.45</td>
<td>0.29</td>
<td>0.18</td>
<td>-0.32</td>
<td>-0.3</td>
</tr>
<tr>
<td></td>
<td>(-8.83)</td>
<td>(-1.10)</td>
<td>(0.62)</td>
<td>(0.33)</td>
<td>(-0.63)</td>
<td>(-0.15)</td>
</tr>
</tbody>
</table>
Table III

Characteristics-adjusted long-run returns of volume-price momentum portfolios

This table reports the returns of the "early" and "late" stage strategies of Lee and Swaminathan (2000). At the end of each month stocks are sorted into five volume quintiles based on ADJTURN\textsubscript{t}. These volume sorts are intersected with quintile sorts on MOM\textsubscript{t}, resulting in 25 momentum-volume portfolios. Returns of stocks in these portfolios are equally weighted, and the portfolios are held for five years. The "late" strategy buys low volume winners and shorts high volume losers. The "early" strategy buys high volume winners and shorts low volume losers. The resulting sequence of five-year "late" and "early" return series is then averaged in event time. The table reports the cumulative event time returns within the first, second, ..., fifth, and second to fifth holding years. In Panel A returns are unadjusted. In Panel B returns are size and book-to-market-adjusted, in Panel C book-to-market and turnover-adjusted. Results are based on the NYSE/AMEX/NASDAQ sample 1964-1999. t-statistics, reported in parentheses, are based on autocorrelation- and heteroskedasticity consistent Newey-West standard errors with 11 lags (47 for the years 2-5 results).

<table>
<thead>
<tr>
<th>Holding Year in Event Time</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>2 - 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Early</td>
<td>12.72</td>
<td>2.39</td>
<td>1.46</td>
<td>1.09</td>
<td>-1.93</td>
<td>3.01</td>
</tr>
<tr>
<td></td>
<td>(4.26)</td>
<td>(0.98)</td>
<td>(0.66)</td>
<td>(0.44)</td>
<td>(-0.81)</td>
<td>(0.33)</td>
</tr>
<tr>
<td>Late</td>
<td>2.98</td>
<td>-5.22</td>
<td>-3.92</td>
<td>-3.56</td>
<td>-2.92</td>
<td>-15.62</td>
</tr>
<tr>
<td></td>
<td>(1.17)</td>
<td>(-2.21)</td>
<td>(-1.97)</td>
<td>(-1.64)</td>
<td>(-1.01)</td>
<td>(-2.43)</td>
</tr>
<tr>
<td>Early</td>
<td>12.82</td>
<td>4.09</td>
<td>2.55</td>
<td>0.86</td>
<td>-1.58</td>
<td>5.92</td>
</tr>
<tr>
<td></td>
<td>(5.28)</td>
<td>(2.07)</td>
<td>(1.34)</td>
<td>(0.39)</td>
<td>(-0.80)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>Late</td>
<td>6.54</td>
<td>-1.91</td>
<td>-2.33</td>
<td>-1.22</td>
<td>-0.51</td>
<td>-5.97</td>
</tr>
<tr>
<td></td>
<td>(3.61)</td>
<td>(-1.13)</td>
<td>(-1.45)</td>
<td>(-0.62)</td>
<td>(-0.18)</td>
<td>(-0.87)</td>
</tr>
<tr>
<td>Early</td>
<td>11.08</td>
<td>1.43</td>
<td>-0.08</td>
<td>-1.46</td>
<td>-3.80</td>
<td>-3.91</td>
</tr>
<tr>
<td></td>
<td>(6.14)</td>
<td>(1.02)</td>
<td>(-0.04)</td>
<td>(-0.70)</td>
<td>(-2.02)</td>
<td>(-0.48)</td>
</tr>
<tr>
<td>Late</td>
<td>9.39</td>
<td>0.65</td>
<td>1.06</td>
<td>1.52</td>
<td>0.96</td>
<td>4.20</td>
</tr>
<tr>
<td></td>
<td>(6.05)</td>
<td>(0.47)</td>
<td>(0.81)</td>
<td>(0.94)</td>
<td>(0.42)</td>
<td>(0.61)</td>
</tr>
</tbody>
</table>
### Table IV

Momentum and long-run changes in breadth of ownership: cross-sectional regressions

The dependent variable is the average $\Delta$BREADTH (in percent) over the four quarters from $t-3$ to $t$, in percent. In panel A it is regressed on contemporaneous MOM6 ($k=0$), reported in the first column, and lagged MOM6 ($k=4,..,16$) in the other columns, where $k$ denotes the lag in quarters. In panel B the regression includes additional control variables, measured at end of quarter $t-4$ (BM, LOGSZ, ADJTURN), or $t$ ($\Delta$HOLD). In panels A and B the dependent variable $\Delta$BREADTH is based on the mutual funds sample, in panel C the institutional investor (13F) sample is used. Cross-sectional regressions are run each quarter $t$ within size quintile subsamples, defined by time $t-4$ market capitalization. Coefficients are then averaged across size subsamples in each cross-section. The table reports the time-series means of these averaged coefficients. Coefficient standard errors are based on the time-series standard deviation of the coefficient estimates, in the usual Fama-McBeth (1973) fashion, adjusted for autocorrelation and heteroskedasticity using the Newey-West procedure. The sample period is 1980 to 2000.

#### Panel A: $\Delta$BREADTH$_{MUT}$ regressed on MOM6

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
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<tbody>
<tr>
<td>MOM6$_{k}$</td>
<td>0.200</td>
<td>0.155</td>
<td>-0.011</td>
<td>-0.025</td>
<td>-0.016</td>
</tr>
<tr>
<td>(6.55)</td>
<td>(10.47)</td>
<td>(-0.86)</td>
<td>(-1.52)</td>
<td>(-1.51)</td>
<td></td>
</tr>
<tr>
<td>Average adj. $R^2$</td>
<td>5.24%</td>
<td>4.34%</td>
<td>0.48%</td>
<td>0.50%</td>
<td>0.26%</td>
</tr>
</tbody>
</table>

#### Panel B: $\Delta$BREADTH$_{MUT}$ regressed on MOM6 and control variables

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>4</th>
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<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>MOM6$_{k}$</td>
<td>0.100</td>
<td>0.185</td>
<td>0.004</td>
<td>-0.020</td>
<td>-0.014</td>
</tr>
<tr>
<td>(4.52)</td>
<td>(12.26)</td>
<td>(0.59)</td>
<td>(-1.70)</td>
<td>(-1.73)</td>
<td></td>
</tr>
<tr>
<td>BM$_{t-4}$</td>
<td>-0.021</td>
<td>-0.004</td>
<td>-0.012</td>
<td>-0.011</td>
<td>-0.012</td>
</tr>
<tr>
<td>(-4.27)</td>
<td>(-0.59)</td>
<td>(-1.93)</td>
<td>(-1.91)</td>
<td>(-2.08)</td>
<td></td>
</tr>
<tr>
<td>LOGSZ$_{t-4}$</td>
<td>-0.068</td>
<td>0.003</td>
<td>0.032</td>
<td>0.019</td>
<td>0.009</td>
</tr>
<tr>
<td>(-9.30)</td>
<td>(0.55)</td>
<td>(3.79)</td>
<td>(2.02)</td>
<td>(0.96)</td>
<td></td>
</tr>
<tr>
<td>ADJTURN$_{t-4}$</td>
<td>-0.006</td>
<td>-0.012</td>
<td>-0.012</td>
<td>-0.012</td>
<td>-0.012</td>
</tr>
<tr>
<td>(-1.72)</td>
<td>(-2.95)</td>
<td>(-2.58)</td>
<td>(-2.26)</td>
<td>(-2.16)</td>
<td></td>
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<tr>
<td>$\Delta$HOLD$_{MUT,t}$</td>
<td>0.091</td>
<td>0.112</td>
<td>0.111</td>
<td>0.111</td>
<td>0.109</td>
</tr>
<tr>
<td>(4.95)</td>
<td>(5.73)</td>
<td>(5.54)</td>
<td>(5.54)</td>
<td>(5.46)</td>
<td></td>
</tr>
<tr>
<td>Average adj. $R^2$</td>
<td>31.09%</td>
<td>27.55%</td>
<td>23.31%</td>
<td>21.32%</td>
<td>20.15%</td>
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#### Panel C: Alternative definition of breadth of ownership: $\Delta$BREADTH$_{INST}$

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<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>MOM6$_{k}$</td>
<td>0.299</td>
<td>0.366</td>
<td>0.094</td>
<td>0.052</td>
<td>0.021</td>
</tr>
<tr>
<td>(8.00)</td>
<td>(17.50)</td>
<td>(4.96)</td>
<td>(2.22)</td>
<td>(0.75)</td>
<td></td>
</tr>
<tr>
<td>BM$_{t-4}$</td>
<td>-0.088</td>
<td>-0.061</td>
<td>-0.059</td>
<td>-0.041</td>
<td>-0.036</td>
</tr>
<tr>
<td>(-9.46)</td>
<td>(-5.02)</td>
<td>(-4.98)</td>
<td>(-3.60)</td>
<td>(-3.49)</td>
<td></td>
</tr>
<tr>
<td>LOGSZ$_{t-4}$</td>
<td>-0.167</td>
<td>0.053</td>
<td>0.123</td>
<td>0.115</td>
<td>0.098</td>
</tr>
<tr>
<td>(-11.73)</td>
<td>(5.00)</td>
<td>(10.63)</td>
<td>(9.01)</td>
<td>(7.95)</td>
<td></td>
</tr>
<tr>
<td>ADJTURN$_{t-4}$</td>
<td>-0.014</td>
<td>-0.022</td>
<td>-0.024</td>
<td>-0.026</td>
<td>-0.031</td>
</tr>
<tr>
<td>(-1.73)</td>
<td>(-2.02)</td>
<td>(-2.07)</td>
<td>(-2.01)</td>
<td>(-2.06)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$HOLD$_{MUT,t}$</td>
<td>0.071</td>
<td>0.098</td>
<td>0.098</td>
<td>0.098</td>
<td>0.097</td>
</tr>
<tr>
<td>(7.01)</td>
<td>(12.00)</td>
<td>(11.41)</td>
<td>(11.14)</td>
<td>(11.40)</td>
<td></td>
</tr>
<tr>
<td>Average adj. $R^2$</td>
<td>31.69%</td>
<td>25.78%</td>
<td>23.16%</td>
<td>21.68%</td>
<td>20.54%</td>
</tr>
</tbody>
</table>
Table V
Momentum and long-run changes in the share of institutional holdings: cross-sectional regressions

The dependent variable is the average ΔHOLD (in percent) over the four quarters from \(t-3\) to \(t\), in percent. In panel A it is regressed on contemporaneous MOM6 \((k=0)\), reported in the first column, and lagged MOM6 \((k=4,..,16)\) in the other columns, where \(k\) denotes the lag in quarters. In panel B the regression includes additional control variables, measured at end of quarter \(t\)-4 (BM, LOGSZ, ADJTURN), or \(t\) (ΔBREADTH). In panels A and B the dependent variable ΔHOLD is based on the mutual funds sample, in panel C the institutional investor (13F) sample is used. Cross-sectional regressions are run each quarter \(t\) within size quintile subsamples, defined by time \(t-4\) market capitalization. Coefficients are then averaged across size subsamples in each cross-section. The table reports the time-series means of these averaged coefficients. Coefficient standard errors are given by the time-series standard deviation of the coefficient estimates, in the usual Fama-McBeth (1973) fashion, adjusted for autocorrelation and heteroskedasticity using the Newey-West procedure. The sample period is 1980 to 2000.

<table>
<thead>
<tr>
<th>(k = ) Lag of MOM6 regressor in quarters</th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: ΔHOLD(_{INST}) regressed on MOM6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MOM6(_{t,k})</td>
<td>1.244</td>
<td>0.152</td>
<td>-0.413</td>
<td>-0.138</td>
<td>-0.105</td>
</tr>
<tr>
<td>(6.65) (1.65) (-5.30) (-2.18) (-2.42)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average adj. R(^2)</td>
<td>3.70%</td>
<td>1.02%</td>
<td>0.68%</td>
<td>0.32%</td>
<td>0.10%</td>
</tr>
<tr>
<td>Panel B: ΔHOLD(_{INST}) regressed on MOM6 and control variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MOM6(_{t,k})</td>
<td>0.352</td>
<td>-0.407</td>
<td>-0.374</td>
<td>-0.090</td>
<td>-0.057</td>
</tr>
<tr>
<td>(2.30) (-5.78) (-7.94) (-2.31) (-1.91)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BM(_{t-4})</td>
<td>0.071</td>
<td>0.120</td>
<td>0.029</td>
<td>-0.013</td>
<td>-0.037</td>
</tr>
<tr>
<td>(1.61) (3.34) (0.76) (-0.32) (-0.97)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LOGSZ(_{t-4})</td>
<td>-0.210</td>
<td>-0.155</td>
<td>-0.295</td>
<td>-0.324</td>
<td>-0.269</td>
</tr>
<tr>
<td>(-3.32) (-5.40) (-6.88) (-9.12) (-9.67)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADJTURN(_{t-4})</td>
<td>0.009</td>
<td>-0.077</td>
<td>-0.069</td>
<td>-0.053</td>
<td>-0.028</td>
</tr>
<tr>
<td>(0.31) (-2.07) (-2.19) (-1.93) (-0.93)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔBREADTH(_{INST,t})</td>
<td>3.656</td>
<td>3.407</td>
<td>2.975</td>
<td>2.679</td>
<td>2.420</td>
</tr>
<tr>
<td>(18.69) (21.30) (22.24) (21.15) (20.20)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average adj. R(^2)</td>
<td>24.69%</td>
<td>24.30%</td>
<td>22.18%</td>
<td>20.31%</td>
<td>18.94%</td>
</tr>
</tbody>
</table>
### Table VI

**Decomposition of changes in breadth: entry and exit of institutional investors**

In panel A the dependent variable is the average IN (in percent) over four quarters from $t-3$ to $t$, in percent, in panel B it is the average OUT, calculated from the institutional investor (13F) sample, where IN is the number of institutions entering a new long position in the stock, and OUT is the number of institutions selling off its entire holdings in the stock. It is regressed on contemporaneous MOM6$^-$ and MOM6$^+$ ($k=0$), reported in the first column, and lagged ($k=4,..,16$) in the other columns, where $k$ denotes the lag in quarters. The regression includes additional control variables (coefficients not shown), measured at end of quarter $t-4$ (BM, LOGSZ, ADJTURN), or $t$ (ΔHOLDINST). Cross-sectional regressions are run each quarter $t$ within size quintile subsamples, defined by time $t-4$ market capitalization. Coefficients are then averaged across size subsamples in each cross-section. The table reports the time-series means of these averaged coefficients. Coefficient standard errors are given by the time-series standard errors of the coefficient estimates, in the usual Fama-McBeth (1973) fashion, adjusted for autocorrelation and heteroskedasticity using the Newey-West procedure. The sample period is 1980 to 2000.

<table>
<thead>
<tr>
<th>$k$ = Lag of MOM6 regressors in quarters</th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: IN$_t$ regressed on MOM6$^-$, MOM6$^+$, and control variables (not shown)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MOM6$_{k^-}$</td>
<td>-0.363</td>
<td>0.199</td>
<td>-0.085</td>
<td>-0.083</td>
<td>-0.148</td>
</tr>
<tr>
<td>($-9.13$)</td>
<td>(8.45)</td>
<td>($-1.76$)</td>
<td>($-2.00$)</td>
<td>($-2.46$)</td>
<td></td>
</tr>
<tr>
<td>MOM6$_{k^+}$</td>
<td>0.284</td>
<td>0.166</td>
<td>0.017</td>
<td>0.002</td>
<td>0.007</td>
</tr>
<tr>
<td>(8.29)</td>
<td>(8.85)</td>
<td>(0.84)</td>
<td>(0.10)</td>
<td>(0.29)</td>
<td></td>
</tr>
<tr>
<td>Average adj. $R^2$</td>
<td>28.50%</td>
<td>29.52%</td>
<td>36.44%</td>
<td>39.51%</td>
<td>41.18%</td>
</tr>
<tr>
<td><strong>Panel B: OUT$_t$ regressed on MOM6$^-$, MOM6$^+$, and control variables (not shown)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MOM6$_{k^-}$</td>
<td>-0.764</td>
<td>-0.329</td>
<td>-0.160</td>
<td>-0.124</td>
<td>-0.087</td>
</tr>
<tr>
<td>($-12.42$)</td>
<td>($-10.81$)</td>
<td>($-4.36$)</td>
<td>($-4.07$)</td>
<td>($-3.66$)</td>
<td></td>
</tr>
<tr>
<td>MOM6$_{k^+}$</td>
<td>0.017</td>
<td>-0.148</td>
<td>-0.072</td>
<td>-0.054</td>
<td>-0.015</td>
</tr>
<tr>
<td>(0.62)</td>
<td>($-11.43$)</td>
<td>($-4.09$)</td>
<td>($-2.71$)</td>
<td>($-0.59$)</td>
<td></td>
</tr>
<tr>
<td>Average adj. $R^2$</td>
<td>43.29%</td>
<td>32.21%</td>
<td>38.06%</td>
<td>41.97%</td>
<td>44.38%</td>
</tr>
</tbody>
</table>
### Table VII

**Entry and exit when momentum investors are excluded**

In panel A the dependent variable is the average XIN (in percent) over four quarters from \( t-3 \) to \( t \), in percent, in panel B it is the average XOUT. XIN and XOUT are defined like IN and OUT in table VI, with the exception that institutions classified as IN-momentum investors are not counted for IN, and those classified as OUT investors are not counted for OUT. Both variables are regressed on contemporaneous MOM6\(^{-}\) and MOM6\(^{+}\) \((k=0)\), reported in the first column, and lagged \((k=4,..,16)\) in the other columns, where \( k \) denotes the lag in quarters. The regression includes additional control variables (coefficients not shown), measured at end of quarter \( t-4 \) (BM, LOGSZ, ADJTURN), or \( t \) (\( \Delta \)HOLD\(_{\text{inot}} \)). Cross-sectional regressions are run each quarter \( t \) within size quintile subsamples, defined by time \( t-4 \) market capitalization. Coefficients are then averaged across size subsamples in each cross-section. The table reports the time-series means of these averaged coefficients. Coefficient standard errors are given by the time-series standard errors of the coefficient estimates, in the usual Fama-McBeth (1973) fashion, adjusted for autocorrelation and heteroskedasticity using the Newey-West procedure. The sample period is 1981-2000.

\( k = \text{Lag of MOM6 regressors in quarters} \)

<table>
<thead>
<tr>
<th>Panel A: XIN(_{t}) regressed on MOM6(^{-}), MOM6(^{+}), and control variables (not shown)</th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>MOM6(_{t-k}^{-})</td>
<td>-0.275</td>
<td>0.061</td>
<td>-0.032</td>
<td>-0.036</td>
<td>-0.106</td>
</tr>
<tr>
<td>(7.90)</td>
<td>(2.85)</td>
<td>(-0.86)</td>
<td>(-1.56)</td>
<td>(-2.76)</td>
<td></td>
</tr>
<tr>
<td>MOM6(_{t-k}^{+})</td>
<td>0.154</td>
<td>0.043</td>
<td>0.002</td>
<td>-0.005</td>
<td>-0.002</td>
</tr>
<tr>
<td>(7.18)</td>
<td>(3.03)</td>
<td>(0.18)</td>
<td>(-0.57)</td>
<td>(-0.14)</td>
<td></td>
</tr>
<tr>
<td>Average adj. R(^2)</td>
<td>24.61%</td>
<td>25.18%</td>
<td>31.94%</td>
<td>35.21%</td>
<td>37.35%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: XOUT(_{t}) regressed on MOM6(^{-}), MOM6(^{+}), and control variables (not shown)</th>
<th>0</th>
<th>4</th>
<th>8</th>
<th>12</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>MOM6(_{t-k}^{-})</td>
<td>-0.556</td>
<td>-0.111</td>
<td>-0.113</td>
<td>-0.106</td>
<td>-0.096</td>
</tr>
<tr>
<td>(-10.87)</td>
<td>(-3.96)</td>
<td>(-3.69)</td>
<td>(-4.80)</td>
<td>(-4.30)</td>
<td></td>
</tr>
<tr>
<td>MOM6(_{t-k}^{+})</td>
<td>0.013</td>
<td>-0.026</td>
<td>-0.036</td>
<td>-0.036</td>
<td>0.002</td>
</tr>
<tr>
<td>(0.66)</td>
<td>(-1.93)</td>
<td>(-2.50)</td>
<td>(-2.70)</td>
<td>(0.13)</td>
<td></td>
</tr>
<tr>
<td>Average adj. R(^2)</td>
<td>36.16%</td>
<td>26.93%</td>
<td>33.47%</td>
<td>36.60%</td>
<td>39.00%</td>
</tr>
</tbody>
</table>
**Figure 1a: Raw Returns**

Cumulative Return

US

UK

Month in Event Time

**Figure 1b: Size and Book-to-Market Adjusted Returns**

Cumulative Return

US

UK

Month in Event Time

**Figure 1: Cumulative Returns of Zero-Investment Momentum Portfolios.** This figure plots event time cumulative returns from a long position in the winner quintile and a short position in the loser quintile (WML). At the end of each month, stocks are ranked and sorted into quintiles by MOM6. Portfolios are formed of stocks in similar quintiles, their returns are equally weighted, and the portfolios are held for five years. The resulting sequence of five-year WML return series is then averaged in event time. In figure 1a returns are unadjusted. In figure 1b returns are adjusted for size and book-to-market, using a matching portfolio approach. The US results are based on NYSE/AMEX/NASDAQ stocks from 1964 to 2000. The UK results are based on London Stock Exchange stocks from 1957 to 2000. Returns are reported in percent. The bold parts of the lines indicate where the average cumulative return is significantly different from zero at a 5% level, with t-statistics are based on autocorrelation- and heteroskedasticity consistent Newey-West standard errors with the number of lags equal to the event time month minus 1.
Figure 2: Change in average breadth of mutual fund ownership for winners and losers after portfolio formation. At the end of each month, stocks are ranked and sorted into quintiles by MOM6. Portfolios are formed of stocks in similar quintiles, and the portfolios are held for five years. In each portfolio $\Delta \text{BREADTH}_{\text{MUT}}$ of the portfolio constituents is equally-weighted. The resulting sequence of five-year average $\Delta \text{BREADTH}_{\text{MUT}}$ series is then averaged in event time. The sample period is 1980-2000. The bold parts of the lines indicate where the average $\Delta \text{BREADTH}_{\text{MUT}}$ is significantly different from zero at a 5% level, with t-statistics based on autocorrelation- and heteroskedasticity-consistent Newey-West standard errors with 11 lags.
Figure 3: Change in the average share of institutional holdings for winners and losers after portfolio formation. At the end of each month, stocks are ranked and sorted into quintiles by MOM6. Portfolios are formed of stocks in similar quintiles, and the portfolios are held for five years. In each portfolio $\Delta \text{HOLD}_{\text{INST}}$ of the portfolio constituents is equally-weighted. The resulting sequence of five-year average $\Delta \text{HOLD}_{\text{INST}}$ series is then averaged in event time. The sample period is 1980-2000. The bold parts of the lines indicate where the average $\Delta \text{HOLD}_{\text{INST}}$ is significantly different from zero at a 5% level, with t-statistics are based on autocorrelation- and heteroskedasticity-consistent Newey-West standard errors with 11 lags.