Journal of Financial Economics 66 (2002) 171–205

JOURNAL OF Financial ECONOMICS

www.elsevier.com/locate/econbase

Breadth of ownership and stock returns☆

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Received 13 March 2001; accepted 27 July 2001

Abstract

We develop a stock market model with differences of opinion and short-sales constraints. When breadth is low—i.e., when few investors have long positions—this signals that the short-sales constraint is binding tightly, and that prices are high relative to fundamentals. Thus reductions in breadth should forecast lower returns. Using data on mutual fund holdings, we find that stocks whose change in breadth in the prior quarter is in the lowest decile of the sample underperform those in the top decile by 6.38% in the twelve months after formation. Adjusting for size, book-to-market, and momentum, the figure is 4.95%.

JEL classification: G12; G14

Keywords: Differences of opinion; Short-sales constraints; Return predictability

1. Introduction

In this paper, we bring new evidence to bear on an asset-pricing hypothesis which has been around a long while, but which has thus far not received much empirical

☆We are grateful to the National Science Foundation and the Division of Research at Harvard Business School for research support. A special thanks to Ken Froot for his insightful comments on our earlier work, which helped to spark our interest in the topic of this paper. Thanks also to the referee (Ken French), to Kent Daniel, Owen Lamont, Toby Moskowitz, and Andrei Shleifer, and to seminar participants at Duke, the University of North Carolina, Yale, the NBER, London Business School, the Federal Reserve Bank of New York, Harvard, Vanderbilt, University of Southern California, Michigan, Princeton, and the University of Texas Finance Festival and the Western Finance Association meetings for helpful suggestions.

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0304-405X/02/$ - see front matter

PII: S0304-405X(02)00223-4

support. The idea, which dates back to Miller (1977), has to do with the combined effects of short-sales constraints and differences of opinion on stock prices. Miller argues that when there are short-sales constraints, a stock's price will reflect the valuations that optimists attach to it, but will not reflect the valuations of pessimists, because the pessimists simply sit out of the market (as opposed to selling short, which is what they would do in an unconstrained setting). Thus short-sales constraints can exert a significant influence on equilibrium prices and expected returns.[1] For example, one interesting cross-sectional implication of Miller's logic is that the greater the divergence in the valuations of the optimists and the pessimists, the higher the price of a stock in equilibrium, and hence the lower the subsequent returns.

This theory seems appealing because it is simple and its premises seem empirically reasonable. First, it is hard to argue with the notion that investors can—even when looking at the same information set—come to sharply varying conclusions about a stock's fundamental value. Indeed, such differences of opinion are perhaps the leading explanation for trading volume in asset markets (e.g., Varian, 1989; Harris and Raviv, 1993; Kandel and Pearson, 1995; Odean, 1998).

Second, with respect to the existence of short-sales constraints, the theory only requires (as we demonstrate explicitly below) that some, not all, investors be constrained. This condition is clearly met at the individual-stock level, even apart from any transaction costs associated with shorting, since many important institutional investors, such as mutual funds, are simply prohibited by their charters from ever taking short positions.[2] Indeed, aggregate short interest is very low for the vast majority of stocks. Dechow et al. (2001) document that over the period 1976–1993 more than 80% of NYSE/AMEX firms had short interest of less than 0.5% of shares outstanding and more than 98% of firms had short interest of less than 5%.

Yet in spite of its surface plausibility and intuitive appeal, the evidence for Miller's theory remains somewhat sparse, even after almost 25 years. Empirical efforts in this area have tended to follow Figlewski (1981), who tests the theory by looking at the relationship between short interest and subsequent returns. The basis for this test is the assumption that one can use "the recorded level of actual short interest as a proxy for the amount of short selling there would have been if it had not been constrained, and therefore, the amount of adverse information that was excluded

[1] Other theoretical work on the implications of short-sales constraints includes Harrison and Kreps (1978), Jarrow (1980), Diamond and Verrecchia (1987), Allen et al. (1993), Morris (1996), and Hong and Stein (2003). In contrast to Miller (1977), some of these papers (e.g., Diamond and Verrecchia, and Hong and Stein) are more in the efficient-markets tradition, and have nothing to say about predictability in returns. This is because they assume complete arbitrage by rational investors who adjust their expectations to incorporate any effects of short-sales constraints.

[2] Almazan et al. (1999) document that roughly 70% of mutual funds explicitly state (in Form N-SAR that they file with the SEC) that they are not permitted to sell short. This is obviously a lower bound on the fraction of funds that never take short positions. Relatedly, Koski and Pontiff (1999) find that 79% of equity mutual funds make no use of derivatives whatsoever (either futures or options) suggesting that funds are also not finding synthetic ways to take short positions.

from the market price." (Figlewski and Webb, 1993, p. 762). Among the papers that attempt to forecast returns with short interest are Brent et al. (1990), Figlewski and Webb (1993), Woolridge and Dickinson (1994), Asquith and Meulbroek (1995), and Dechow et al. (2001).

However, this approach has a couple of important limitations. First, as noted above, the majority of stocks have virtually no short interest outstanding at any given point in time. Thus if the test design involves tracking the abnormal returns of a portfolio of high-short-interest stocks, this portfolio will by definition be small, thereby potentially reducing the power of any tests, as well as calling into question the generalizability of the results. Second, and relatedly, the key identifying assumption in this literature—that one can use short interest as a proxy for the amount of negative information excluded from the market price—is on fragile ground. Variation across stocks in short interest may instead reflect variation in the transactions costs of shorting, perhaps because some stocks have greater institutional ownership and thus have more of their shares available for lending (D'Avolio, 2002). If so, a stock with a low or zero value of short interest may simply be one that is difficult or costly to short, which could potentially translate into more, rather than less, negative information being held off the market. As we demonstrate more formally below, this kind of reasoning implies that there need be no clear-cut relationship between short interest and subsequent returns.

Our goal in this paper is to devise a sharper and more powerful test of Miller's theory. To do so, we observe that a more reliable proxy for how tightly short-sales constraints bind (and hence for the amount of negative information withheld from the market) can be constructed by looking at data on breadth of ownership, where breadth is defined roughly as the number of investors with long positions in a particular stock. Specifically, when breadth for a stock is lower, more investors are sitting on the sidelines, with their pessimistic valuations not registered in the stock's price. Thus our basic insight is that breadth of ownership is a valuation indicator.

This insight yields two types of testable hypotheses. First, breadth should, by itself, be useful for forecasting returns. Specifically, reductions in breadth should forecast lower subsequent returns, and conversely, increases in breadth should forecast higher returns. Second, one might expect breadth to be positively correlated with other valuation indicators—i.e., with other variables that indicate that price is low relative to fundamentals and as a result also forecast increased risk-adjusted returns. Possible candidates include book-to-market (Fama and French, 1992; Lakonishok et al., 1994), earnings-to-price (Basu, 1983), and momentum (Jegadeesh and Titman, 1993).

Using quarterly data on mutual fund holdings over the period 1979–1998 and a variety of different tests, we find evidence supportive of both of these hypotheses. With respect to the first hypothesis, we find that those stocks whose change in breadth in the prior quarter places them in the lowest decile of the sample underperform those in the top change-in-breadth decile by 3.82% in the first six months after portfolio formation and by 6.38% in the first 12 months. With respect to the second hypothesis, we find that breadth in any given quarter responds in a positive fashion to both earnings-to-price and recent price momentum (measured by returns over the prior year). The correlation between breadth and the prior year's return is particularly strong. As we discuss in more detail below, this correlation suggests that short-sales constraints play an important role in the momentum phenomenon. Still, even after controlling for size, book-to-market, and momentum, we continue to find that our trading strategy based on change-in-breadth earns significant profits with abnormal returns of 2.92% in the first six months after formation and 4.95% in the first 12 months.

The mutual fund data are useful for our purposes because they represent comprehensive coverage of the stockholdings of a large, well-defined segment of the investor population. Moreover, as noted above, we are probably on safe ground in assuming that mutual funds rarely, if ever, take short positions. This lack of shorting among mutual funds is crucial if we are to use breadth as a proxy for negative information held off the market. It implies that if we observe a given fund not having a long position in a particular stock, we can equate this with the fund sitting on the sidelines, i.e., having no position at all.

At the same time, using the mutual fund data is not without its drawbacks. Ideally, we would have data that covered *all potential investors subject to short-sales constraints*. Because our data do not cover all investors, our measure of breadth is in part influenced by movements in the relative holdings of mutual funds vs. other classes of investors. Consider the following example. Suppose there are one hundred shares of stock outstanding and one hundred mutual funds. In the first period, each fund owns one share. In Scenario A, in the second period, 50 of the funds own two shares each and 50 of the funds have reduced their holdings to zero. This scenario corresponds precisely to a reduction in breadth of the sort we want to capture. The aggregate holdings of the mutual fund sector are unchanged from the first to the second period, but within the mutual fund sector, the shares are less broadly held.

However, in Scenario B, in the second period, 50 of the funds own one share each, 50 of the funds have holdings of zero, and 50 shares have migrated into the hands of 50 other investors, perhaps individuals, who now also hold one share each. Given that our data covers only mutual funds, we will record this as a reduction in breadth as well. But it is clearly not what the theory has in mind—all that has happened in this scenario is that shares have on net moved out of the mutual fund sector and into the hands of individuals.

This sort of measurement error opens the door to alternative interpretations of our results. In particular, one might hypothesize that changes in breadth are able to forecast returns not because of the theoretical mechanism that we are interested in, but rather because mutual fund managers have better stock-picking skills than individuals. If this is so, the movement of shares from mutual funds to individuals in Scenario B above would be a bearish signal simply because fund managers are smarter than individuals. Recent work by Chen et al. (2000) lends some support to this hypothesis. They show that changes in the mutual fund sector's aggregate holdings of a stock have some forecasting power for returns—when funds are on net buyers of a stock, the stock tends to outperform over the next year or so, and vice versa.

In our tests, we attempt to control for the effect identified by Chen et al. (2000). For example, in the context of a regression that uses our change-in-breadth variable to forecast returns, we add as a control their changes-in-aggregate-fund-holdings variable. The goal is to have the breadth measure pick up only the kind of variation described in Scenario A of the example, and not the kind in Scenario B. As it turns out, the breadth measure survives this kind of control essentially intact.

Nevertheless, the fact remains that our measure of breadth is based not on the entire investing universe—as the theory suggests it should be—but rather on just the mutual-fund sector. This is an important limitation, and it suggests interpreting our results with some caution. It is hard to completely rule out the possibility that our results do not really reflect binding short-sales constraints, but rather some kind of superior stock-picking skill on the part of mutual fund managers that operates in such a way that it is not well summarized by the Chen et al. (2000) changes-in-aggregate-fund-holdings variable.

The remainder of the paper is organized as follows. Section 2 builds a simple model that shows how differences of opinion and short-sales constraints affect individual stock prices. Although the model is based on Miller's ideas, it is formulated somewhat differently, in such a way as to make the logic behind our empirical tests as transparent as possible. Section 3 describes the data we use to conduct these tests. Our main empirical results are in Sections 4 and 5. Section 6 concludes.

2. The model

Our model considers the pricing of a single stock and has two dates. There is a total supply of Q shares of the stock, which at time 2 pays a terminal dividend of $F + \varepsilon$ per share, where ε is a normally distributed shock, with a mean of zero and variance of one. At time 1, there are two classes of traders in the stock. First, there is a group of buyers who can only take long positions. For concreteness, one might interpret the buyers as mutual funds, who are generally prohibited from going short. There is a continuum of such buyers, with valuations (i.e., estimates of the time-2 dividend) uniformly distributed on the interval $[F - H, F + H]$. Thus on average the buyers have the right valuation, but there is heterogeneity across the group, with the degree of this heterogeneity parameterized by H.

The total mass of the buyer population is normalized to one, and each buyer has constant-absolute-risk-aversion (CARA) utility, with a risk tolerance of γ_B. Thus in the absence of short-sales constraints, a buyer i with valuation of V_i would have demand equal to $\gamma_B(V_i - P)$. However, given the constraint, the observed demand is $\text{Max}\left[0, \gamma_B(V_i - P)\right]$.

The second class of traders is a group of fully rational arbitrageurs who can take either long or short positions. One might think of these arbitrageurs as hedge funds who face no restrictions on shorting and who are adept at minimizing any frictional costs associated with such transactions. The arbitrageurs also have CARA utility, and their aggregate risk tolerance is γ_A, so that their total demand is given by $\gamma_A(F-P)$.

If there were no short-sales constraints facing the buyers, market-wide demand at time 1, denoted by Q^{DU}, would be given by

$$Q^{\mathrm{DU}} = \frac{1}{2H}\int_{F-H}^{F+H} \gamma_B(V_i - P)\,\mathrm{d}V_i + \gamma_A(F-P). \tag{1}$$

Performing the integration indicated in Eq. (1), and setting the demand Q^{DU} equal to the supply Q, it is easily shown that the time-1 price in this unconstrained case, given by P^{U}, satisfies

$$P^{\mathrm{U}} = F - \frac{Q}{\gamma_A + \gamma_B}. \tag{2}$$

As can be seen, when there are no short-sales constraints, the heterogeneity of the buyers has no effect on price: the optimists and the pessimists offset each other, and the price is the same as would prevail if all the buyers had the rational-expectations valuation of exactly F.

On the other hand, in the presence of a binding short-sales constraint, market-wide demand, now denoted by Q^{DC}, is given by

$$Q^{\mathrm{DC}} = \frac{1}{2H}\int_{P}^{F+H} \gamma_B(V_i - P)\,\mathrm{d}V_i + \gamma_A(F-P). \tag{3}$$

After integrating and imposing the market clearing condition that $Q^{\mathrm{DC}} = Q$, we obtain a quadratic that can be solved (see Appendix A for details) to yield the following expression for the price in the case of a binding constraint, P^{C}:

$$P^{\mathrm{C}} = F + H + \frac{2H}{\gamma_B}\left(\gamma_A - \sqrt{\gamma_A^2 + \gamma_A\gamma_B + \gamma_B\frac{Q}{H}}\right). \tag{4}$$

Observe, however, that the short-sales constraint only binds if the price in the unconstrained case, P^{U}, exceeds the valuation of the most pessimistic buyer, $F-H$. That is, the short-sales constraint only binds if H is sufficiently large; in particular, if $H \geqslant Q/(\gamma_A+\gamma_B)$. Thus overall, the equilibrium price, which we denote by P^*, is given by:

$$P^* = \begin{cases} P^{\mathrm{U}} & \text{if} \quad H < \dfrac{Q}{\gamma_A+\gamma_B}, \\ P^{\mathrm{C}} & \text{if} \quad H \geqslant \dfrac{Q}{\gamma_A+\lambda_B}. \end{cases} \tag{5}$$

The equilibrium price P^* has a variety of intuitive properties, which we establish formally in Appendix A. First, P^* is always greater than the unconstrained price P^{U}. Moreover, P^* is an increasing function of the heterogeneity parameter H, which means that the expected return on the stock between time 1 and time 2, $(F-P^*)$, decreases with H. This is true for any finite value of γ_A; as the risk tolerance of the arbitrageurs goes to infinity, both P^* and P^{U} approach F, so that expected returns with or without short-sales constraints converge to zero. Note that we are using "expected return" here as a synonym for ($F-P^*$), the difference between price and fundamentals. But since our model does not include any factor risks of the sort seen in classical pricing models such as the CAPM or APT, ($F-P^*$) is more precisely thought of as the *net factor-risk-adjusted expected return*. That is, in a classical setting with no priced factor risks, arbitrageurs' risk tolerance would be infinite and ($F-P^*$) would be zero.

The directional effect of arbitrageurs' risk tolerance γ_A on the stock price can go either way. When H is relatively large compared to Q (more precisely, when $H \geqslant 4Q/\gamma_B$), the stock price exceeds the fundamental value F, and the arbitrageurs take short positions. In this case, any increase in γ_A drives the stock price down, back towards F. In contrast, when H is small compared to Q, the stock price is below the fundamental value F, and the arbitrageurs take long positions. In this case, an increase in γ_A represents an increase in risk-sharing capacity, and pushes the stock price up.

2.1. Breadth and expected returns

For the purposes of our empirical work, we are most interested in establishing the connection between expected returns and the breadth of ownership among those investors subject to short-sales constraints—i.e., the buyers. We define breadth of ownership B as the fraction of buyers who are long the stock:

$$B = \text{Min}\left[\frac{F + H - P^*}{2H}, 1\right]. \tag{6}$$

Breadth is bounded between zero and one. It is one when the price is less than or equal to the valuation of the most pessimistic buyers, and it approaches zero when the price approaches the valuation of the most optimistic buyers.

We begin by asking what kind of relationship between breadth and expected returns is induced by variations in the parameter H. In Appendix A, we establish

Proposition 1. *As the divergence of opinion H increases, breadth B and the expected return* ($F - P^*$) *both decrease.*

Thus, if we consider a cross-section of stocks that only vary in the degree of divergence of opinion, then those stocks with the lowest values of breadth will also have the lowest expected returns. This is precisely Miller's (1977) intuition.

Of course, if the only source of variation in the model were differences across stocks in H, one could also obtain a clear-cut prediction using short interest. In particular, those stocks with the highest values of H (and hence the lowest expected returns) would also be the most heavily shorted by the arbitrageurs. As a result, high values of short interest (just like low values of breadth) would also forecast lower returns.

However, the link between short interest and expected returns is much less robust than that between breadth and expected returns. This can be seen by considering variations in some of the other parameters of the model. In Appendix A, we show that

Proposition 2. *Cross-stock variation in any of the other model parameters* (γ_A, γ_B, or Q) *induces a positive correlation between breadth and expected returns. Thus regardless of the source of variation, the unconditional correlation between breadth and expected returns is unambiguously positive.*

The intuition behind Proposition 2 is straightforward, and can be seen by looking at Eq. (6). Holding fixed H, breadth is determined completely by $(F - P^*)$—i.e., by the difference between fundamentals and price, or equivalently, by the expected return on the stock. Thus anything that causes the price P^* to go up relative to fundamentals (be it a change in γ_A, γ_B, or Q) will also manifest itself as a reduction in breadth. Moreover, one can think of changes in Q as not literally just supply shocks, but rather as unmodeled changes in investor sentiment that, as in DeLong et al. (1990), induce divergences between prices and fundamentals. The bottom line is that breadth is a robust valuation indicator.

In contrast, consider the relationship between short interest and expected returns induced by cross-stock differences in arbitrageurs' risk tolerance γ_A. In Appendix A, we prove

Proposition 3. *Suppose* $H \geqslant 4Q/\lambda_B$. *In this case,* $P^* \geqslant F$ *so that arbitrageurs take short positions. Moreover, an increase in* γ_A *leads to an increase in short interest. This increase in short interest is accompanied by a decrease in prices and hence by an increase in both breadth and expected returns.*

Thus for H large enough, variations in γ_A induce a positive correlation between short interest and expected returns. This is just the opposite of the correlation induced by variations in H. So while the model produces an unambiguous link between breadth and expected returns, the same is not true for short interest and expected returns. This formalizes the point made in the introduction, namely that there is no good theoretical reason to expect short interest to be a reliable predictor of returns.

2.2. Testable hypotheses

In our empirical work below, we test three specific hypotheses that are implied by Propositions 1 and 2:

Hypothesis 1. *An increase (decrease) in a stock's breadth at time t should forecast higher (lower) returns over some future interval from t to t+k.*

Hypothesis 2. *If there are other time-t variables that are known to be positively related to risk-adjusted future returns (perhaps book-to-market, earnings-to-price, or* *momentum), then breadth at time t should be positively correlated with these predictive variables.*

Hypothesis 3. *After controlling for other known predictors of returns, the ability of breadth at time t to forecast future returns should be reduced though not necessarily eliminated.*

Hypothesis 1 follows directly from Propositions 1 and 2 and needs no further elaboration. Hypothesis 2 is a bit subtler. Recall that whatever the source of variation, breadth is positively related to the risk-adjusted expected return ($F - P^*$) on the stock. This implies that if there are other observable variables that are also good proxies for risk-adjusted expected returns, breadth should be positively correlated with these proxies.

To take a relevant example, suppose there is a non-risk-related momentum effect in stock prices (Jegadeesh and Titman, 1993), so that returns from time t to $t+k$ are positively correlated with returns from $t-k$ to t. In this case, one would expect breadth at time t to be positively related to past returns (i.e., to returns from $t-k$ to t). Thus if a stock's price falls from $t-k$ to t, breadth at time t should fall also. The intuition for this result is as follows. In a world with momentum, a price drop over the interval from $t-k$ to t is a signal that the price at time t is too high relative to fundamentals. Given that the median buyer makes an accurate assessment of fundamentals, this buyer will be more inclined to want to get out of the stock at time t. Or to say it differently, since reductions in breadth are an indication that the short-sales constraint is more binding, the model's implication is that the constraint binds more tightly after a price decline.

Note however, that if a given variable is able to forecast returns solely because it is a proxy for risk, then there would be no reason to expect it to be correlated with movements in breadth. For example, if Fama and French (1992, 1993, 1996) are correct, and book-to-market is purely a risk measure, then one should not expect the short-sales constraint to bind more tightly (i.e., breadth to be lower) in low-book-to-market glamour stocks.

Hypothesis 3 is a direct byproduct of Hypotheses 1 and 2. Continuing with the momentum example, if breadth at time t is correlated with returns from $t-k$ to t, then one should expect breadth to have less forecasting power for future returns once we control for past returns. Of course, from the perspective of someone interested in devising innovative trading strategies, the hope is that the predictive power of the breadth variable is not largely subsumed by a known predictor such as momentum.

3. Data

Our data on mutual fund holdings come from the Mutual Fund Common Stock Holding/Transactions database obtained from CDA/Spectrum. This database contains information on quarterly equity holdings of mutual funds based in the United States from the first quarter of 1979 through the fourth quarter of 1998.

Mutual funds are required by SEC regulation N30-D to disclose their portfolio holdings twice a year. CDA/Spectrum collects data from these filings and supplements the data through voluntary quarterly reports published by the mutual funds for their shareholders.[3] We do not exclude any funds on the basis of their investment objectives.

In each quarter t, we measure breadth of ownership for every stock, denoted BREADTH_t, as the ratio of the number of mutual funds that hold a long position in the stock to the total number of mutual funds in the sample for that quarter. Since our universe of mutual funds evolves over time as new funds are created and existing funds are dissolved, we need to take special care in measuring the change in breadth of ownership, so as to capture the trading activities of existing funds rather than changes in the composition of the universe. (At the beginning of our sample period, 1979Q1, we have data on 582 funds. By the end of the period, 1998Q4, we have data on 8950 funds.) Thus to define the change in breadth of ownership, denoted as $\Delta\text{BREADTH}_t$, we look at only those funds that are in our sample in both quarter t and quarter $t-1$. From this group, we take the number of funds who hold the stock at quarter t minus the number of funds who hold the stock at quarter $t-1$ and divide by the total number of funds in the sample at quarter $t-1$.

In some of our robustness checks, we make use of the fact that $\Delta\text{BREADTH}_t$ can be decomposed as $\Delta\text{BREADTH}_t = \text{IN}_t - \text{OUT}_t$, where IN_t is defined as the fraction of funds in the sample at both quarters $t-1$ and t that have a zero position in the stock at quarter $t-1$ and that open a new position at quarter t, and OUT_t is defined as the fraction of funds in the sample at both quarters $t-1$ and t that completely remove a previously existing position at quarter t.

We also compute a measure of the aggregate stockholdings of all mutual funds, denoted HOLD_t, as the total number of shares held by all mutual funds at the end of quarter t divided by the total number of shares outstanding. We define ΔHOLD_t as the change in aggregate mutual fund stockholdings from the end of quarter $t-1$ to the end of quarter t. The latter of these two variables is identical to that used by Chen et al. (2000) to forecast returns; as noted earlier, it will be one of our key controls.

Data on quarterly stock returns and trading volume are obtained by aggregating monthly stock file data from the Center for Research in Security Prices (CRSP). We follow standard convention and limit our analysis to common stocks of firms incorporated in the United States; these stocks are identified by a CRSP share type code of 10 or 11. LOGSIZE_t is defined as the logarithm of market capitalization calculated from CRSP at the end of quarter t. We obtain data on book value and earnings from S&P COMPUSTAT's annual and quarterly files. Following Fama and French (1993), we define book value as the value of common stockholders' equity, plus deferred taxes and investment tax credit, minus the book value of preferred stock. The book value is then divided by the firm's market capitalization on the day of the firm's fiscal year-end to yield the book-to-market ratio, denoted as BK/MKT_t. For each quarter, we use the value of book-to-market as of the most

[3] Further details on the construction of this database are available in Appendix Aof Wermers (1999).

recent fiscal year-end. For each quarter, we also collect from COMPUSTAT each firm's past-twelve-months cumulative primary earnings per share. This value is divided by the price of the stock at the end of the quarter to give earnings-per-share, denoted E/P_t. We also obtain from CRSP each firm's twelve-month cumulative holding-period return to the end of quarter of t, denoted as $\mathrm{MOM12}_t$.

We use the CRSP monthly tape to calculate share turnover for each month as the total number of shares traded divided by shares outstanding. We sum share turnover over every three months to obtain a quarterly measure of share turnover, denoted $\mathrm{TURNOVER}_t$. Since the dealer nature of the NASDAQ market makes turnover on this exchange hard to compare with turnover on the NYSE and AMEX, we work with a measure of turnover which has been demeaned, allowing for two means each quarter: one for NYSE/AMEX firms and one for NASDAQ firms. The resulting exchange-adjusted turnover variable is denoted $\mathrm{XTURNOVER}_t$.

3.1. Summary statistics

Table 1 shows summary statistics for the variables to be used in our analysis. A few important points stand out. First, in Panel A, we see that the mean value of $\mathrm{BREADTH}_t$ is closely related to market capitalization, ranging from 7.09% for stocks in the top-size quintile (based on NYSE breakpoints), to 0.25% for stocks in the bottom-size quintile. In other words, only a small number of mutual funds hold positions in the lowest-cap stocks at any point in time. The standard deviations of $\mathrm{BREADTH}_t$ and $\Delta\mathrm{BREADTH}_t$ show similar patterns with respect to firm size. This raises the concern that, among the low-cap stocks, we may not have enough meaningful variation in our key right-hand-side variable to find anything. So in our baseline specifications, we eliminate the bottom-quintile stocks from our sample, and focus only on those stocks with market capitalization above the 20th percentile NYSE breakpoint. We do however examine these small-cap stocks separately in one of our robustness checks.

Panels B and C make it clear that we cannot simply use the raw value of $\mathrm{BREADTH}_t$ as an empirical analog to our model's B variable. In levels, $\mathrm{BREADTH}_t$ is effectively a permanent firm characteristic, with a quarterly autocorrelation of 0.99. Not surprisingly, $\mathrm{BREADTH}_t$ is highly correlated with $\mathrm{LOGSIZE}_t$ (contemporaneous correlation = 0.69), as well as with $\mathrm{XTURNOVER}_t$ (correlation = 0.09), which just says that more funds hold large, liquid stocks. Our univariate correlations also pick up a weak tendency for more mutual funds to hold glamour stocks than value stocks; the correlation between $\mathrm{BREADTH}_t$ and $\mathrm{BK/MKT}_t$ is −0.06.

In an effort to purge such firm fixed effects, we work instead with $\Delta\mathrm{BREADTH}_t$. We have also experimented with using a stochastically detrended version of our breadth measure, generated by subtracting from $\mathrm{BREADTH}_t$ an average of its values over the past three quarters. Our results in this case are similar to those using $\Delta\mathrm{BREADTH}_t$, so we do not report them.

Table 1
Summary statistics

The sample includes stocks from the NYSE, AMEX, and NASDAQ between 1979 and 1998. BREADTH_t is the fraction of all mutual funds long the stock at the end of quarter t. $\Delta\text{BREADTH}_t$ is the change in breadth of ownership from the end of quarter $t-1$ to quarter t. IN_t is the fraction of mutual funds in the sample at both quarters $t-1$ and t that have established a new position in a stock at quarter t. OUT_t is the fraction of mutual funds that have completely removed an existing position in a stock at quarter t. ΔHOLD_t is the fraction of shares outstanding of a stock held by mutual funds at the end of quarter t. ΔHOLD_t is the change in the fraction of shares held by mutual funds from the end of quarter $t-1$ to quarter t. LOGSIZE_t is the log of market capitalization measured at the end of quarter t. BK/MKT_t is the most recently available observation of book-to-market ratio at the end of quarter t. E/P_t is past year's earnings per share divided by the price at the end of quarter t. NYSE/AMEX TURNOVER_t is the share turnover in quarter t among stocks listed on NYSE and AMEX. NASDAQ TURNOVER_t is the share turnover in quarter t of stocks listed on NASDAQ. XTURNOVER_t is share turnover demeaned within each quarter by the average turnover for the firm's exchange (either NYSE/AMEX or NASDAQ). MOM12_t is the raw return in the twelve months up to quarter t. Size quintiles are determined using NYSE breakpoints.

Panel A: Means and standard deviations

		All firms	Quintiles 2–5 firms	Quintile 5 (largest) firms	Quintile 4 firms	Quintile 3 firms	Quintile 2 firms	Quintile 1 (smallest) firms
BREADTH_t	Mean	1.29%	2.30%	7.09%	2.56%	1.43%	0.76%	0.25%
	Std. dev.	2.46%	3.12%	5.10%	1.42%	0.93%	0.55%	0.25%
$\Delta\text{BREADTH}_t$	Mean	0.00%	0.00%	−0.02%	−0.01%	0.00%	0.00%	−0.01%
	Std. dev.	0.34%	0.46%	0.91%	0.46%	0.31%	0.20%	0.10%
IN_t	Mean	0.15%	0.27%	0.71%	0.32%	0.20%	0.10%	0.03%
	Std. dev.	0.37%	0.49%	0.87%	0.42%	0.28%	0.18%	0.08%
OUT_t	Mean	0.16%	0.27%	0.73%	0.32%	0.19%	0.10%	0.03%
	Std. dev.	0.30%	0.37%	0.57%	0.29%	0.21%	0.14%	0.07%
HOLD_t	Mean	8.58%	10.90%	10.80%	12.33%	11.39%	9.88%	6.19%
	Std. dev.	8.62%	9.26%	8.37%	9.96%	9.80%	8.73%	7.17%
ΔHOLD_t	Mean	0.12%	0.19%	0.16%	0.16%	0.22%	0.19%	0.05%
	Std. dev.	2.89%	2.55%	1.63%	2.38%	2.61%	2.90%	3.20%
LOGSIZE_t	Mean	5.049	6.424	8.578	7.169	6.206	5.295	3.638
	Std. dev.	1.818	1.341	0.999	0.612	0.565	0.568	0.961
BK/MKT_t	Mean	0.722	0.664	0.620	0.658	0.649	0.697	0.780
	Std. dev.	2.238	0.568	0.463	0.487	0.502	0.675	3.132
E/P_t	Mean	−0.194	0.038	0.068	0.058	0.043	0.005	−0.411
	Std. dev.	0.954	0.127	0.052	0.074	0.107	0.200	1.511
NYSE/AMEX	Mean	15.8%	17.6%	17.7%	18.8%	17.7%	16.3%	12.4%
TURNOVER_t	Std. dev.	15.7%	16.3%	13.8%	16.2%	17.4%	17.2%	14.0%
NASDAQ TURNOVER_t	Mean	29.8%	37.5%	44.0%	42.8%	39.4%	34.7%	25.2%
	Std. dev.	35.6%	42.9%	48.0%	49.5%	45.5%	38.9%	29.6%
MOM12_t	Mean	20.2%	24.3%	24.0%	23.5%	24.2%	24.8%	15.7%
	Std. dev.	62.9%	51.7%	36.2%	44.2%	50.7%	61.1%	72.8%
	No. of obs.	204,829	103,747	16,740	19,927	27,216	39,864	101,082

Panel B: Contemporaneous correlations (using only firms above 20th percentile in size)

	$BREADTH_t$	$\Delta BREADTH_t$	IN_t	OUT_t	$HOLD_t$	$\Delta HOLD_t$	$LOGSIZE_t$	BK/MKT_t	E/P_t	$XTURNOVER_t$	$MOM12_t$
$BREADTH_t$		0.056	0.781	0.718	0.080	0.010	0.691	−0.062	0.084	0.090	−0.011
$\Delta BREADTH_t$			0.217	−0.336	0.026	0.185	0.014	−0.025	0.013	0.002	0.167
IN_t				0.632	0.127	0.106	0.596	−0.082	0.062	0.213	0.096
OUT_t					0.059	0.122	0.533	−0.043	0.047	0.231	−0.079
$HOLD_t$						0.179	0.231	−0.207	−0.022	0.293	0.071
$\Delta HOLD_t$							0.023	−0.023	0.023	−0.019	0.128
$LOGSIZE_t$								−0.160	0.092	0.027	0.069
BK/MKT_t									0.123	−0.100	−0.113
E/P_t										−0.092	0.001
$XTURNOVER_t$											0.149
$MOM12_t$											

Panel C: Autocorrelations and cross-autocorrelations (using only firms above 20th percentile in size)

	$BREADTH_{t-1}$	$\Delta BREADTH_{t-1}$	IN_{t-1}	OUT_{t-1}	$HOLD_{t-1}$	$\Delta HOLD_{t-1}$	$LOGSIZE_{t-1}$	BK/MKT_{t-1}	E/P_{t-1}	$XTURNOVER_{t-1}$	$MOM12_{t-1}$
$BREADTH_t$	0.989	0.061	0.779	0.712	0.078	0.009	0.697	−0.063	0.079	0.090	−0.019
$\Delta BREADTH_t$	−0.092	0.028	−0.017	−0.100	−0.025	0.046	−0.008	−0.012	0.019	−0.009	0.125
IN_t	0.751	0.088	0.714	0.630	0.097	0.020	0.587	−0.080	0.053	0.200	0.072
OUT_t	0.766	−0.006	0.695	0.718	0.092	−0.026	0.548	−0.057	0.057	0.232	−0.037
$HOLD_t$	0.076	0.038	0.126	0.054	0.962	0.168	0.229	−0.206	−0.033	0.286	0.090
$\Delta HOLD_t$	−0.016	0.028	0.004	−0.026	−0.100	−0.040	0.010	−0.013	0.018	−0.020	0.075
$LOGSIZE_t$	0.690	0.019	0.591	0.530	0.226	0.015	0.988	−0.154	0.087	0.022	0.016
BK/MKT_t	−0.060	−0.041	−0.090	−0.039	−0.201	−0.034	−0.164	0.907	0.107	−0.099	−0.161
E/P_t	0.074	−0.003	0.063	0.042	−0.037	−0.001	0.090	0.143	0.798	−0.079	0.010
$XTURNOVER_t$	0.092	0.024	0.205	0.197	0.304	0.033	0.033	−0.099	−0.088	0.849	0.180
$MOM12_t$	−0.035	0.147	0.072	−0.096	0.038	0.134	0.003	−0.049	0.028	0.127	0.711

4. Determinants of ΔBREADTH

In Table 2, we investigate the determinants of $\Delta\text{BREADTH}_t$. We have two goals in doing so. First, as noted in the introduction, we need to be aware of any correlation between $\Delta\text{BREADTH}_t$ and the Chen-Jegadeesh-Wermers (2000) variable ΔHOLD_t; when we turn to forecasting returns, we will need to control for the fact that some movements in our breadth variable do not reflect just a rearrangement of stockholdings *within* the mutual-fund sector (which is what our model would have us look at) but rather, an overall movement of shares *in and out of* the sector. Second, in an effort to test Hypothesis 2, we want to see to what extent $\Delta\text{BREADTH}_t$ is capturing the information in other well-known predictors of stock returns.

In Panel A, we present the results of regressing $\Delta\text{BREADTH}_t$ against the following five variables: ΔHOLD_t, LOGSIZE_t, BK/MKT_t, MOM12_t, and XTURNOVER_t. The regressions are implemented as follows. We run a separate regression each quarter for each of the four size classes. (Recall that we are dropping the smallest quintile of stocks from our baseline analysis.) We then average the regression coefficients across quarters, as in Fama and MacBeth (1973), to produce a result for each size class. Finally, the coefficients for each size class are averaged together to produce an overall result for the whole universe. The reason that we do things this way (rather than running a single cross-sectional regression for all stocks in our sample each quarter) is that, as can be seen from Panel A of Table 1, there is much more variance in $\Delta\text{BREADTH}_t$ among larger stocks. Were we to run a single regression for all stocks pooled together, this heteroskedasticity would cause the larger stocks to exert a disproportionate influence on the overall results. This issue becomes even more important when we use $\Delta\text{BREADTH}_t$ to forecast returns, and we will take an analogous approach to dealing with it.

The key conclusions from Panel A of Table 2 are as follows. First, as expected, there is a significant positive correlation between $\Delta\text{BREADTH}_t$ and ΔHOLD_t. This correlation would seem to be purely mechanical—when the mutual fund sector as a whole owns a larger percentage of a given stock, it is likely that a greater number of funds will be long the stock—and does not speak to any of our hypotheses. Nevertheless, as stressed above, it is something we will need to control for in our subsequent tests.

Perhaps more interestingly, there is also a strong positive correlation between $\Delta\text{BREADTH}_t$ and the momentum variable, MOM12_t. Given that momentum is a predictor of future returns (Jegadeesh and Titman, 1993), this finding is consistent with Hypothesis 2. Moreover, the finding suggests that the momentum phenomenon is itself linked to the existence of binding short-sales constraints. In particular, consider a situation in which, for a given stock, past returns are strongly negative, so that the rational expectation is that future returns will be relatively low. The obvious question is why this effect is not arbitraged away. The results in Table 2 suggest that some would-be arbitrageurs are held in check by their inability to go short. That is, many mutual funds do get completely out of a stock with negative momentum, but since they cannot go any further than just getting out, they are unable to immediately drive prices all the way down to the point where they ought to go. This line of

Table 2
Determinants of ΔBREADTH
The sample includes stocks from the NYSE, AMEX, and NASDAQ between 1979 and 1998 with a market capitalization above the 20th percentile using NYSE breakpoints. The dependent variable is $\Delta BREADTH_t$, the change in the breadth of ownership for a stock in quarter t. $\Delta HOLD_t$ is the change in aggregate mutual fund holdings of a stock in quarter t. $LOGSIZE_t$ is the log of market capitalization at the end of quarter t. BK/MKT_t is the most recently available observation of book-to-market ratio at the end of quarter t. E/P_t is past year's earnings per share divided by the price at the end of quarter t. MOM12 is the raw return from the beginning of quarter $t-3$ to the end of quarter t. $XTURNOVER_t$ is share turnover demeaned within each quarter by the average turnover for the firm's exchange (either NYSE/AMEX or NASDAQ). Size quintiles are determined using NYSE breakpoints. The coefficients reported in the table are time-series means of the coefficients from cross-sectional regressors run every quarter (i.e., Fama-MacBeth (1973) coefficients). The coefficients for the full sample are averages of the size subsample coefficients. t-statistics, which are in parentheses, are adjusted for serial correlation and heteroskedasticity.

Panel A: Specification including BK/MKT_t

	$\Delta HOLD_t$	$LOGSIZE_t$	BK/MKT_t	MOM12	$XTURNOVER_t$	Average R^2 (%)	No. of qtrs.
Size quintile 2	0.0504	0.0002	0.0000	0.0008	−0.0001	33.3	79
	(7.86)	(2.66)	(0.34)	(13.46)	(0.41)		
Size quintile 3	0.0729	0.0005	−0.0001	0.0015	−0.0006	34.8	79
	(7.80)	(3.75)	(0.98)	(12.51)	(2.65)		
Size quintile 4	0.1164	0.0006	−0.0001	0.0025	−0.0004	33.1	79
	(7.40)	(2.73)	(1.22)	(11.45)	(1.22)		
Size quintile 5	0.2560	−0.0001	−0.0004	0.0068	−0.0005	32.0	79
	(7.65)	(0.20)	(2.02)	(11.29)	(0.44)		
Full sample	0.1239	0.0003	−0.0002	0.0029	−0.0004	33.1	79
	(7.97)	(2.05)	(2.06)	(13.04)	(1.12)		

Panel B: Specification including E/P_t

	$\Delta HOLD_t$	$LOGSIZE_t$	E/P_t	MOM12	$XTURNOVER_t$	Average R^2 (%)	No. of qtrs.
Size quintile 2	0.0503	0.0002	0.0003	0.0008	0.0000	34.8	79
	(7.86)	(2.64)	(2.74)	(12.88)	(0.15)		
Size quintile 3	0.0729	0.0005	0.0005	0.0015	−0.0006	33.1	79
	(7.79)	(3.64)	(2.94)	(12.41)	(2.44)		
Size quintile 4	0.1159	0.0006	0.0011	0.0025	−0.0003	31.8	79
	(7.42)	(2.74)	(2.73)	(11.41)	(0.91)		
Size quintile 5	0.2575	−0.0001	0.0018	0.0068	−0.0005	32.9	79
	(7.68)	(0.16)	(1.69)	(11.73)	(0.42)		
Full sample	0.1242	0.0003	0.0009	0.0029	−0.0003	33.2	79
	(7.98)	(2.07)	(3.25)	(13.33)	(0.99)		

argument is closely related to the observation that the bulk of profits in momentum strategies appear to come from the short side of the trade (Hong et al., 2000). It also fits nicely with D'Avolio's (2002) finding that the explicit transactions costs of shorting—as measured by whether the underlying stock is hard to borrow—are, all else equal, greater for stocks with negative momentum.

On the other hand, Hypothesis 2 strikes out with respect to another well-known return predictor, the book-to-market ratio. The correlation between $\Delta\text{BREADTH}_t$ and BK/MKT_t actually goes the wrong way (it is negative) although it is statistically insignificant for all but the largest size quintile and implies only a tiny economic effect. One possible interpretation for this outcome is that Fama and French (1992, 1993, 1996) are right and book-to-market captures risk, not mispricing relative to fundamentals. Or said somewhat more agnostically, to the extent that there is some risk-adjusted predictability associated with the book-to-market effect, it is not great enough to create a significant pent-up desire by investors to go short.

An alternative rationalization is that our sample of mutual funds is not representative of all investors in terms of its behavior toward the book-to-market attribute. Recall that ideally, our model would have us look at breadth across all investors subject to short-sales constraints. If, for example, the number of mutual funds that invest primarily in glamour stocks exceeds the number focusing on value stocks, this could generate the sort of result seen in Panel A of Table 2, even if across the entire investing population, the correlation between (appropriately measured) changes breadth and book-to-market were in fact positive.

In Panel B of Table 2, we rerun the same basic exercise, keeping everything the same except replacing BK/MKT_t with the earnings-to-price ratio E/P_t.[4] (The correlation between these two measures of fundamentals-to-price is not all that high in our sample, at only 0.12.) This change produces results more in line with Hypothesis 2. The coefficient on E/P_t has the predicted positive sign, and is statistically significant across all size classes. So, continuing with the above logic, perhaps earnings-to-price contains more information about non-risk-related movements in expected returns than does book-to-market.

At the same time, it is important to recognize that even though E/P_t is statistically significant in Panel B of Table 2, its economic impact is small relative to that of the momentum variable. Specifically, across the full sample, a one-standard-deviation move in E/P_t has roughly one-thirteenth the effect on $\Delta\text{BREADTH}_t$ as a one-standard deviation move in MOM12_t. So the first-order conclusion from Table 2 is that of the variables that are known to predict returns, momentum seems to be the most closely linked with binding short-sales constraints.

However, some readers have suggested a caveat to this interpretation of the evidence in Table 2. In our model, we implicitly assume that all buyers are continuously monitoring every stock. Thus if a given buyer sits out of a stock, it is because he has a well-thought-out valuation for that stock that is below the market price. But more realistically, it may be that a stock is simply "not on the radar screen" of some mutual fund managers (Merton, 1987). This possibility is underscored by the data in Table 1 Panel A, which shows that on average across quintiles two through five, the typical stock is only held by 2.30% of mutual funds. If so, one needs to worry about the following alternative interpretation: perhaps

[4] The E/P_t variable has some large outliers, especially on the negative side. To prevent them from dominating the results, we truncate these outliers at their three-standard-deviation values.

positive momentum in a given stock is associated with an increase in breadth not because it leads to a change in the distribution of valuations among those buyers already actively following the stock, but rather because it enlarges the set of buyers who pay attention to the stock.

To address this point, we decompose $\Delta BREADTH_t$ as $\Delta BREADTH_t = IN_t - OUT_t$, and examine the determinants of IN_t and OUT_t separately. The caveat above applies most directly to IN_t, since if a fund first opens a position in a stock at t, we do not know if it was out of the stock at $t-1$ because its valuation was too low, or because it simply was not following the stock. In contrast, OUT_t is conceptually cleaner from this perspective. After all, if a fund closes an existing position in a stock at t, it probably was following the stock at $t-1$, given that it owned the stock at that time.

In Table 3, we reproduce the regressions in Table 2 Panel A, except that we replace $\Delta BREADTH_t$ on the left-hand side with IN_t (in Panel A) and OUT_t (in Panel B). The MOM12 variable now attracts significant positive coefficients in the IN_t regressions and significant negative coefficients in the OUT_t regressions. But more strikingly, the coefficients in the OUT_t regressions are substantially larger in absolute magnitude—roughly five times larger over the full sample. Thus while both IN_t and OUT_t contribute something to the positive correlation between $\Delta BREADTH_t$ and MOM12, the lion's share of the contribution is coming from OUT_t. This helps to allay the concern that the positive correlation between $\Delta BREADTH_t$ and MOM12 reflects just an increased-attention phenomenon. Or said differently, the results in Tables 2 and 3 are, when taken together, most consistent with the following story: when a stock has negative momentum, an increased number of funds that were previously owners of it actively reevaluate it in such a way that they choose to sell out completely and move to the sidelines.

Table 3 also sheds further light on why the correlation between $\Delta BREADTH_t$ and BK/MKT_t is so weak. The correlation between OUT_t and BK/MKT_t is actually strongly negative, which is what one might have expected based on Hypothesis 2—as a stock becomes more glamour-like, an increasing number of funds who were already actively monitoring it choose to get out of it. But this effect is more or less exactly offset by a strong negative correlation between IN_t and BK/MKT_t, which runs counter to Hypothesis 2, and which might possibly reflect the increased-attention phenomenon—as a stock becomes more glamour-like, perhaps an increasing number of funds start to notice it for the first time.

5. Using ΔBREADTH to forecast returns

5.1. Portfolio sorts

We now turn to Hypotheses 1 and 3, which involve using the ΔBREADTH variable to forecast stock returns. In Tables 4 and 5, this forecasting is done with

Table 3

Determinants of IN and OUT

The sample includes stocks from the NYSE, AMEX, and NASDAQ between 1979 and 1998 with a market capitalization above the 20th percentile using NYSE breakpoints. The dependent variables are IN_t and OUT_t. IN_t is the fraction of mutual funds in the sample at both quarters $t-1$ and t that have established a new position in a stock at quarter t. OUT_t is the fraction of mutual funds that have completely removed an existing position in a stock at quarter t. $\Delta HOLD_t$ is the change in aggregate mutual fund holdings of a stock in quarter t. $LOGSIZE_t$ is the log of market capitalization at the end of quarter t. BK/MKT_t is the most recently available observation of book-to-market ratio at the end of quarter t. MOM12 is the raw return from the beginning of quarter $t-3$ to the end of quarter t. $XTURNOVER_t$ is share turnover demeaned within each quarter by the average turnover for the firm's exchange (either NYSE/AMEX or NASDAQ). The coefficients are the averages of size subsample coefficients, where the size subsample coefficients are time-series means of the coefficients from cross-sectional regressors run every quarter (i.e., Fama-MacBeth (1973) coefficients) within each size quintile. t-statistics, which are in parentheses, are adjusted for serial correlation and heteroskedasticity.

	$\Delta HOLD_t$	$LOGSIZE_t$	BK/MKT_t	MOM12	$XTURNOVER_t$	Average R^2 (%)	No. of qtrs.
Panel A: Determinants of IN							
Size quintile 2	0.0260	0.0009	−0.0001	0.0001	0.0033	36.3	79
	(7.56)	(9.05)	(2.38)	(3.58)	(8.03)		
Size quintile 3	0.0370	0.0013	−0.0004	0.0004	0.0052	38.0	79
	(7.23)	(15.53)	(7.32)	(3.73)	(8.45)		
Size quintile 4	0.0596	0.0021	−0.0004	0.0005	0.0086	38.2	79
	(7.38)	(15.69)	(5.59)	(3.14)	(8.35)		
Size quintile 5	0.1279	0.0050	−0.0013	0.0007	0.0201	55.8	79
	(7.26)	(23.26)	(7.01)	(2.12)	(8.14)		
Full sample	0.0626	0.0024	−0.0005	0.0004	0.0093	42.1	79
	(8.01)	(24.08)	(8.50)	(3.32)	(8.87)		
Panel B: Determinants of OUT							
Size quintile 2	−0.0217	0.0006	−0.0001	−0.0006	0.0033	33.9	79
	(6.82)	(11.72)	(3.79)	(11.39)	(7.94)		
Size quintile 3	−0.0328	0.0007	−0.0003	−0.0010	0.0056	39.4	79
	(7.03)	(16.30)	(7.66)	(12.58)	(8.49)		
Size quintile 4	−0.0512	0.0013	−0.0003	−0.0018	0.0089	39.4	79
	(6.03)	(15.96)	(4.51)	(14.32)	(8.87)		
Size quintile 5	−0.1216	0.0041	−0.0008	−0.0053	0.0199	53.0	79
	(6.98)	(20.00)	(4.46)	(15.75)	(9.12)		
Full sample	−0.0568	0.0017	−0.0004	−0.0022	0.0094	41.4	79
	(7.24)	(23.17)	(6.79)	(17.93)	(9.45)		

portfolio sorts. Consider first Panel A of Table 4. Here our aim is to forecast raw returns. In the four left-hand columns of the panel, we sort stocks into ten portfolios every quarter based simply on ΔBREADTH. We do so by assigning stocks into decile classes of ΔBREADTH, with the decile breakpoints determined separately within each size quintile. We then recombine the deciles across size classes. This

Table 4

Returns to portfolio strategies based on ΔBREADTH

The sample includes stocks from NYSE/AMEX and NASDAQ between 1979 and 1998 with a market capitalization above the 20th percentile using NYSE breakpoints. In each quarter t, stocks are ranked (into deciles) relative to other stocks in their size quintile on the basis of their change in breadth, $\Delta BREADTH_t$. Then for stocks in similar deciles of $\Delta BREADTH_t$ across the size quintiles, an equal-weighted portfolio is formed and the performance is tracked over four quarters. In each quarter t, for stocks in size quintiles, residual $\Delta BREADTH_t$ is formed by regressing $\Delta BREADTH_t$ on $\Delta HOLD_t$, the change in aggregate holdings of mutual funds in that quarter. Stocks are ranked (into deciles) relative to other stocks in their size quintile on the basis of residual $\Delta BREADTH_t$. Then for stocks in similar deciles of residual $\Delta BREADTH_t$, an equal-weighted portfolio is formed and the performance is tracked over four quarters. This table reports the average returns of the portfolios in each decile of the two sorts on $\Delta BREADTH_t$ and residual $\Delta BREADTH_t$ along with the difference in the returns of portfolios in deciles 10 and 1, P10−P1. Panels A, B, and C present these results using raw returns, size/book-to-market adjusted returns, and size/book-to-market/momentum adjusted returns, respectively. t-statistics, which are in parentheses, are adjusted for serial-correlation using a Newey-West estimator with lags of up to four quarters.

Cumulative returns after		Sort on ΔBREADTH				Sort on residual ΔBREADTH			
		1 Quarter	2 Quarters	3 Quarters	4 Quarters	1 Quarter	2 Quarters	3 Quarters	4 Quarters
Panel A: Raw returns									
Decile	1	2.93%	5.83%	9.27%	13.48%	2.99%	6.03%	9.53%	14.07%
		(3.07)	(3.49)	(3.94)	(4.47)	(3.08)	(3.56)	(4.03)	(4.60)
	2	3.35%	7.19%	11.50%	16.52%	3.84%	7.87%	11.96%	16.65%
		(3.44)	(4.18)	(4.78)	(5.27)	(4.04)	(4.54)	(4.96)	(5.47)
	3	3.80%	8.02%	12.04%	16.41%	3.64%	8.04%	12.55%	17.45%
		(4.27)	(4.83)	(5.10)	(5.60)	(3.99)	(4.85)	(5.17)	(5.77)
	4	4.11%	8.56%	12.80%	17.69%	3.89%	8.29%	12.79%	17.69%
		(4.83)	(5.30)	(5.44)	(5.93)	(4.61)	(5.28)	(5.47)	(5.95)
	5	3.65%	8.04%	12.67%	17.95%	3.91%	8.21%	12.39%	17.55%
		(4.43)	(5.00)	(5.46)	(6.04)	(4.38)	(4.94)	(5.29)	(5.83)
	6	4.10%	8.41%	12.90%	17.94%	3.85%	8.25%	12.84%	17.49%
		(4.42)	(4.86)	(5.15)	(5.76)	(4.53)	(5.05)	(5.44)	(6.11)
	7	3.83%	8.21%	12.53%	17.29%	4.03%	8.33%	12.62%	17.13%
		(4.35)	(4.99)	(5.32)	(5.79)	(4.47)	(4.88)	(5.34)	(5.71)
	8	4.45%	9.08%	13.63%	18.33%	4.12%	8.42%	13.08%	17.88%
		(4.56)	(4.98)	(5.49)	(5.93)	(4.28)	(4.61)	(5.11)	(5.51)
	9	4.39%	8.89%	13.76%	18.57%	4.34%	8.72%	13.27%	18.00%
		(4.57)	(4.76)	(5.16)	(5.70)	(4.74)	(4.73)	(5.17)	(5.65)

Table 4 (*continued*)

Cumulative returns after		Sort on ΔBREADTH				Sort on residual ΔBREADTH			
		1 Quarter	2 Quarters	3 Quarters	4 Quarters	1 Quarter	2 Quarters	3 Quarters	4 Quarters
	10	4.95%	9.66%	14.78%	19.86%	4.94%	9.80%	14.96%	20.32%
		(4.47)	(4.68)	(5.04)	(5.33)	(4.43)	(4.85)	(5.17)	(5.54)
	P10−P1	2.02%	3.82%	5.51%	6.38%	1.96%	3.77%	5.43%	6.25%
		(3.96)	(4.66)	(4.52)	(4.08)	(3.97)	(5.01)	(5.24)	(4.67)
Panel B: Size and book-to-market-adjusted returns									
Decile	1	−0.99%	−2.24%	−3.03%	−3.52%	−0.95%	−2.08%	−2.86%	−3.04%
		(4.40)	(6.10)	(5.21)	(4.35)	(4.49)	(6.02)	(6.12)	(4.72)
	2	−0.61%	−1.03%	−1.13%	−1.02%	−0.13%	−0.35%	−0.62%	−0.79%
		(3.82)	(4.30)	(4.29)	(2.49)	(0.80)	(1.13)	(1.60)	(1.89)
	3	−0.12%	−0.13%	−0.60%	−0.99%	−0.32%	−0.20%	−0.17%	−0.14%
		(0.91)	(0.45)	(1.48)	(1.88)	(2.28)	(0.77)	(0.58)	(0.33)
	4	−0.02%	0.10%	−0.14%	−0.07%	−0.12%	−0.04%	0.01%	0.08%
		(0.13)	(0.33)	(0.44)	(0.17)	(0.60)	(0.13)	(0.02)	(0.29)
	5	−0.21%	−0.24%	−0.08%	0.15%	−0.07%	−0.05%	−0.35%	−0.06%
		(1.44)	(0.95)	(0.23)	(0.29)	(0.39)	(0.18)	(1.01)	(0.12)
	6	−0.02%	0.13%	0.21%	0.43%	−0.08%	0.05%	0.22%	−0.09%
		(0.11)	(0.39)	(0.46)	(0.91)	(0.40)	(0.17)	(0.55)	(0.17)
	7	−0.03%	−0.06%	−0.18%	−0.25%	0.03%	0.02%	−0.16%	−0.39%
		(0.17)	(0.23)	(0.48)	(0.45)	(0.17)	(0.09)	(0.55)	(1.02)
	8	0.53%	0.99%	1.09%	0.97%	0.19%	0.24%	0.46%	0.49%
		(2.82)	(3.38)	(3.08)	(2.51)	(1.09)	(0.86)	(1.31)	(1.44)
	9	0.41%	0.75%	1.19%	1.28%	0.41%	0.65%	0.85%	0.75%
		(2.30)	(2.24)	(2.51)	(2.57)	(3.04)	(2.10)	(2.21)	(1.92)
	10	1.05%	1.65%	2.56%	2.87%	1.01%	1.75%	2.61%	3.19%
		(3.08)	(2.65)	(2.85)	(2.62)	(2.87)	(3.00)	(3.26)	(3.13)
	P10−P1	2.04%	3.89%	5.59%	6.39%	1.96%	3.83%	5.47%	6.24%
		(4.28)	(5.15)	(4.69)	(4.33)	(4.35)	(5.49)	(5.57)	(4.96)

Panel C: Size, book-to-market and momentum-adjusted returns

Decile	1	−0.57%	−1.66%	−2.31%	−2.62%	−0.55%	−1.48%	−2.19%	−2.21%
		(2.73)	(5.02)	(4.51)	(3.77)	(2.82)	(4.70)	(5.29)	(3.90)
	2	−0.49%	−0.76%	−0.79%	−0.62%	−0.03%	−0.20%	−0.36%	−0.60%
		(3.19)	(3.51)	(3.60)	(1.92)	(0.21)	(0.68)	(1.01)	(1.65)
	3	−0.05%	−0.07%	−0.63%	−0.93%	−0.22%	−0.07%	−0.01%	0.11%
		(0.47)	(0.28)	(1.77)	(2.02)	(1.63)	(0.30)	(0.02)	(0.29)
	4	0.04%	0.27%	0.07%	0.17%	0.03%	0.15%	0.14%	0.32%
		(0.25)	(1.05)	(0.29)	(0.47)	(0.20)	(0.65)	(0.55)	(1.14)
	5	−0.23%	−0.34%	−0.22%	0.06%	−0.13%	−0.20%	−0.52%	−0.31%
		(1.90)	(1.55)	(0.74)	(0.15)	(0.89)	(0.87)	(1.92)	(0.87)
	6	−0.01%	0.08%	0.10%	0.25%	−0.09%	0.02%	0.12%	−0.07%
		(0.08)	(0.26)	(0.24)	(0.58)	(0.52)	(0.07)	(0.31)	(0.14)
	7	−0.04%	−0.11%	−0.17%	−0.35%	−0.04%	−0.07%	−0.32%	−0.62%
		(0.25)	(0.42)	(0.54)	(0.69)	(0.25)	(0.36)	(1.18)	(1.94)
	8	0.45%	0.85%	0.89%	0.84%	0.19%	0.11%	0.31%	0.36%
		(2.82)	(3.26)	(2.56)	(2.24)	(1.23)	(0.45)	(0.93)	(1.24)
	9	0.17%	0.42%	0.81%	0.78%	0.22%	0.44%	0.67%	0.45%
		(0.99)	(1.35)	(1.82)	(1.78)	(1.74)	(1.67)	(1.91)	(1.22)
	10	0.71%	1.26%	2.18%	2.32%	0.62%	1.30%	2.16%	2.58%
		(2.50)	(2.39)	(2.92)	(2.54)	(2.02)	(2.53)	(3.21)	(3.06)
	P10−P1	1.28%	2.92%	4.49%	4.95%	1.17%	2.78%	4.35%	4.78%
		(3.13)	(4.26)	(4.45)	(3.93)	(2.77)	(4.07)	(4.90)	(4.28)

Table 5
Returns to portfolio strategies based on ΔBREADTH, disaggregated by size
The sample includes stocks from NYSE/AMEX and NASDAQ between 1979 and 1998. In each quarter t, for stocks in size quintiles, residual $\Delta\text{BREADTH}_t$ is formed by regressing $\Delta\text{BREADTH}_t$ on ΔHOLD_t, the change in aggregate holdings of mutual funds in that quarter. Stocks are ranked (into deciles) relative to other stocks in their size quintile on the basis of residual $\Delta\text{BREADTH}_t$. Then for stocks in similar deciles of residual $\Delta\text{BREADTH}_t$, an equal-weighted portfolio is formed and the performance is tracked over four quarters. This table reports the average returns of the portfolios in deciles 1 and 10 along with the difference in the returns of portfolios in deciles 10 and 1, P10–P1. Panels A, B, and C present these results using raw returns, size/book-to-market adjusted returns, and size/book-to-market/momentum adjusted returns, respectively. t-statistics, which are in parentheses, are adjusted for serial-correlation using a Newey-West estimator with lags of up to four quarters.

Cumulative returns after	Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters
Panel A: Raw returns, sort on residual ΔBREADTH										
Decile 1	8.48%	19.45%	5.32%	14.56%	5.40%	11.62%	7.00%	15.29%	7.93%	15.87%
	(3.67)	(4.39)	(2.68)	(3.81)	(3.07)	(3.98)	(3.72)	(4.94)	(5.36)	(5.42)
10	9.09%	18.64%	10.46%	20.96%	9.67%	19.86%	9.24%	20.05%	9.49%	20.71%
	(3.93)	(4.08)	(4.25)	(4.62)	(4.82)	(5.66)	(4.53)	(5.10)	(4.90)	(6.17)
P10–P1	1.22%	−1.07%	5.15%	6.40%	4.27%	8.24%	2.24%	4.76%	1.56%	4.84%
	(1.57)	(0.71)	(5.88)	(3.36)	(3.81)	(5.31)	(1.96)	(2.49)	(1.45)	(3.18)
Panel B: Size and book-to-market-adjusted returns, sort on residual ΔBREADTH										
Decile 1	−1.27%	−0.61%	−2.61%	−2.77%	−2.73%	−5.06%	−1.13%	−2.06%	−0.76%	−1.79%
	(2.13)	(0.65)	(5.72)	(2.47)	(4.08)	(5.40)	(1.50)	(2.08)	(1.36)	(1.96)
10	−0.06%	−1.49%	2.52%	3.50%	1.53%	3.10%	1.40%	3.23%	0.90%	2.83%
	(0.11)	(1.44)	(3.34)	(2.87)	(2.16)	(2.41)	(1.57)	(1.94)	(1.25)	(2.79)
	1.22%	−0.86%	5.13%	6.27%	4.26%	8.15%	2.53%	5.28%	1.66%	4.62%
P10–P1	(1.69)	(0.60)	(6.40)	(3.58)	(3.94)	(5.51)	(2.34)	(2.88)	(1.52)	(3.12)
Panel C: Size, book-to-market, and momentum-adjusted returns, sort on residual ΔBREADTH										
Decile 1	−1.12%	−0.74%	−1.96%	−2.01%	−1.90%	−3.79%	−0.62%	−1.20%	−0.53%	−1.44%
	(2.09)	(0.85)	(5.16)	(2.00)	(2.88)	(4.20)	(0.88)	(1.23)	(0.94)	(1.61)
10	−0.27%	−1.42%	2.01%	3.00%	1.17%	2.44%	1.06%	2.63%	0.28%	1.89%
	(0.52)	(1.54)	(2.87)	(2.81)	(1.85)	(2.21)	(1.48)	(1.89)	(0.49)	(2.33)
P10–P1	0.87%	−0.66%	3.97%	5.02%	3.07%	6.23%	1.68%	3.82%	0.80%	3.33%
	(1.35)	(0.51)	(5.03)	(3.14)	(2.86)	(4.43)	(1.95)	(2.44)	(0.87)	(2.66)

procedure ensures that within each ΔBREADTH decile, we will have stocks of roughly the same size. The procedure is necessary because, as we have seen, there is much more variation in ΔBREADTH across large stocks; if we instead did an unconditional ranking on ΔBREADTH independent of size, the extreme (high and low ΔBREADTH) deciles would be dominated by large stocks.

In the four right-hand columns of the panel, we do a similar assignment of stocks to deciles, except here we sort on "RESIDUAL ΔBREADTH," defined as the residual in a univariate regression of $\Delta\text{BREADTH}_t$ against ΔHOLD_t. The rationale for sorting on RESIDUAL ΔBREADTH, as opposed to simply on ΔBREADTH, is that, as discussed above, our model implies that we want to isolate changes in the composition of stockholdings *within* the mutual-fund sector, as distinct from an overall movement of shares *in and out of* the sector.

In either case, we track returns out one, two, three, and four quarters after the portfolio formation date. We have also done some experimentation with horizons beyond four quarters. Although it appears that excess returns continue to accrue to our strategies after the four-quarter mark, the effects are relatively weaker and increasingly clouded by the statistical noise that accompanies longer horizons.

As can be seen, the results for raw returns in Panel A of Table 4 are striking and not much affected by whether we sort on ΔBREADTH or RESIDUAL ΔBREADTH. For example, two quarters after portfolio formation, the (P10−P1) portfolio that is long the top-decile-ΔBREADTH stocks and short the bottom-decile-ΔBREADTH stocks has earned 3.82%, which translates into an annualized rate of return of 7.79%. Four quarters after portfolio formation, the (P10−P1) portfolio is up by 6.38%. Using RESIDUAL ΔBREADTH instead of ΔBREADTH to do the sorts, the corresponding numbers are 3.77% after two quarters (7.68% on an annualized basis) and 6.25% after four quarters. In all cases the results are strongly statistically significant.

In Panel B of Table 4, we redo everything in Panel A using returns adjusted to control for size and book-to-market. To implement this control, we create portfolio benchmarks using a characteristics-based procedure similar to Daniel et al. (1997). At the end of every quarter, we assign stocks to market-cap quintiles based on NYSE breakpoints. Within each size quintile, stocks are further ranked into subquintiles, based on their book-to-market ratios (again using NYSE breakpoints). This yields a total of 25 groups of stocks. For each group, the equal-weighted holding-period return is computed (for one, two, three, and four-quarter horizons) and is used as the benchmark portfolio return. The size and book-to-market adjusted return for a stock over any holding period is then the holding-period return for that stock in excess of the holding-period return on the portfolio to which it belongs.

Finally, Panel C of Table 4 reports results using size, book-to-market, and momentum-adjusted returns. This is a three-dimensional extension of the adjustment in Panel B. In addition to the 25 groupings based on size and book-to-market, stocks are further ranked into momentum quintiles each quarter, based on their raw returns over the prior twelve months, resulting in a total of 125 portfolio groups. The equal-weighted holding-period return for each of the 125 benchmark portfolios is then calculated, and the adjusted return for a stock is defined as its holding-period return less the holding-period return on the portfolio to which it belongs.

As can be seen, the size and book-to-market adjustment in Panel B of Table 4 does not make any perceptible difference. For example, when forming portfolios based on ΔBREADTH, the (P10−P1) return is 6.38% after four quarters with raw returns in Panel A. With the size and book-to-market adjustment the four-quarter return is 6.39%. The fact that the adjustment has little effect should not be surprising in light of the results in Table 2: recall that ΔBREADTH is virtually uncorrelated with book-to-market and only weakly correlated with size.

Of course, the results in Table 2 also suggest that adding a momentum control to our measure of returns might potentially make more of a difference, since ΔBREADTH and MOM12 are quite strongly correlated. And indeed, this is evident in Panel C of Table 4, where returns are size, book-to-market, and momentum-adjusted. Now after two quarters the (P10−P1) return is down to 2.92% (5.93% on an annualized basis) and after four quarters it is 4.95%. Thus the momentum control reduces the amount of predictability by roughly 20–25% as compared to the case of raw returns. Nevertheless, the effect that remains continues to be of a magnitude that, at a minimum, would appear to be economically interesting.

In Table 5, we disaggregate Table 4's results by size. We also for the first time look at those stocks in the first-size quintile, which we have been leaving out of our baseline sample. Panel A gives a condensed treatment of the raw-returns case. Panels B and C cover size and book-to-market-adjusted returns, and size, book-to-market, and momentum-adjusted returns respectively. To save space, we only look at sorts based on RESIDUAL ΔBREADTH. As might be inferred from Table 4, the results using sorts based on simple ΔBREADTH are very similar.

The picture that emerges from Table 5 can be summarized as follows. First, there is no evidence that RESIDUAL ΔBREADTH has any ability to forecast returns among the smallest stocks—the (P10−P1) differentials in quintile 1 are statistically and economically close to zero. While this is not surprising given the relative lack of variation in ΔBREADTH in quintile 1, it does mean that by choosing to exclude the quintile-1 stocks from our baseline specifications we have made our results look stronger than they otherwise would.

Second, once one moves beyond quintile 1, the results look robust in the sense that there is significant predictability based on RESIDUAL ΔBREADTH across all the remaining size classes, no matter which measure of returns one looks at. At the same time, the magnitude of this predictability appears greater among the smaller stocks in quintiles 2 and 3 (especially quintile 3) than among the larger stocks in quintiles 4 and 5, though we do not have the power to make statements about these differences being statistically significant. For example, in Panel A with raw returns, the four-quarter (P10−P1) return is: 6.40% in quintile 2; 8.24% in quintile 3; 4.76% in quintile 4; and 4.84% in quintile 5. In Panel C with size, book-to-market, and momentum-adjusted returns, the corresponding numbers are 5.02%, 6.23%, 3.82%, and 3.33% for quintiles 2, 3, 4, and 5, respectively.

5.2. Fama-MacBeth regressions

As an alternative approach to evaluating the forecasting power of ΔBREADTH, we present in Table 6 a series of Fama-MacBeth (1973) regressions. We implement the Fama-MacBeth technique in much the same way as in Tables 2 and 3. That is, for every specification of interest, we run a separate cross-sectional regression every quarter for every size class. With 79 quarters and four size classes, this gives us a total of 316 regressions. Table 6 then reports the mean coefficients across these 316 regressions, along with the associated *t*-statistics.[5] As before, the rationale for running separate regressions for each size class is the strong tendency for there to be more variance in ΔBREADTH for larger stocks.

In all cases, our dependent variable is now measured in units of raw returns; in this format controls can be added as right-hand-side variables in the regression, so there is no need to use benchmark-adjusted returns on the left-hand-side. There are four panels in Table 6, corresponding to forecast horizons of one, two, three, and four quarters. The patterns are similar across panels, so the basic story can be understood by focusing on just Panel D, which looks at a four-quarter horizon.

In the first column, the only variable used to forecast returns is ΔBREADTH. It enters with a coefficient of 4.47 and a *t*-statistic of 3.51. To get a sense of magnitudes, the coefficient of 4.47 implies that a two-standard deviation spread in ΔBREADTH generates a differential in expected returns of 4.14% over a four-quarter horizon.[6] In the second column, the only right-hand-side variable is the Chen-Jegadeesh-Wermers (2000) variable, ΔHOLD. Consistent with their findings, ΔHOLD is significant on its own, with a coefficient of 0.722 and a *t*-statistic of 3.25. In the third column, we put ΔBREADTH and ΔHOLD in the regression together. Interestingly, the clear winner of this horse race is ΔBREADTH—its coefficient is, at 4.50, almost identical to that in the univariate case. In contrast, the coefficient on ΔHOLD is badly damaged by the addition of ΔBREADTH, falling from 0.722 to 0.207, and becoming statistically insignificant.

Finally, in the fourth column we add several other control variables to the regression: LOGSIZE, BK/MKT, MOM12, and XTURNOVER.[7] As might be expected from what we have already seen in the portfolio sorts, these added controls (especially the MOM12 variable, which enters strongly) reduce, but do not eliminate, the effect of ΔBREADTH. In particular, the coefficient on ΔBREADTH is now 2.93, with a *t*-statistic of 3.18. This implies that, controlling for everything else in the

[5] The standard errors are computed as follows. First, for every quarter, we average the coefficients across size classes, yielding 79 full-sample point estimates—one for each quarter. The standard errors are then based on the time-series serial correlation properties of these 79 estimates, as in the usual Fama-MacBeth application.

[6] From Table 1, Panel A, the standard deviation of ΔBREADTH for quintiles 2–5 is 0.46%. So we have $2 \times 4.47 \times 0.46\% = 4.14\%$.

[7] We include XTURNOVER in our list of controls because a number of recent papers (e.g., Brennan et al., 1998) have found a negative relationship between turnover and expected returns. As can be seen in Table 6, our regressions strongly bear out the existence of this pattern.

Table 6

Forecasting returns with ΔBREADTH: Fama-MacBeth regressions

The sample includes stocks from the NYSE, AMEX, and NASDAQ between 1979 and 1998 with a market capitalization above the 20th percentile using NYSE breakpoints. The dependent variables are raw returns over one to four quarters. $\Delta\text{BREADTH}_t$ is the change in the breadth of ownership for a stock in quarter t. ΔHOLD_t is the change in aggregate mutual fund holdings of a stock in quarter t. LOGSIZE_t is the log of market capitalization at the end of quarter t. BK/MKT_t is the most recently available observation of book-to-market ratio at the end of quarter t. MOM12 is the raw return from the beginning of quarter $t-3$ to the end of quarter t. XTURNOVER_t is share turnover demeaned within each quarter by the average turnover for the firm's exchange (either NYSE/AMEX or NASDAQ). t-statistics, which are in parentheses, are adjusted for serial correlation and heteroskedasticity.

	1. $\Delta\text{BREADTH}_t$ only	2. ΔHOLD_t only	3. $\Delta\text{BREADTH}_t$ and ΔHOLD_t	4. Additional controls
Panel A: Raw returns over one quarter				
$\Delta\text{BREADTH}_t$	2.045		2.055	1.187
	(3.72)		(3.49)	(2.67)
ΔHOLD_t		0.257	0.093	0.072
		(2.90)	(1.25)	(1.17)
LOGSIZE_t				−0.003
				(1.01)
BK/MKT_t				0.008
				(1.71)
MOM12_t				0.029
				(4.02)
XTURNOVER_t				−0.038
				(2.49)
No. of quarters	79	79	79	79
Average R^2	1.2%	0.8%	1.9%	9.5%
Panel B: Raw returns over two quarters				
$\Delta\text{BREADTH}_t$	3.502		3.552	2.022
	(4.29)		(4.04)	(2.76)
ΔHOLD_t		0.430	0.119	0.129
		(3.54)	(1.22)	(1.45)
LOGSIZE_t				−0.001
				(0.25)
BK/MKT_t				0.014
				(1.82)
MOM12_t				0.059
				(4.62)
XTURNOVER_t				−0.071
				(2.50)
No. of quarters	79	79	79	79
Average R^2	1.2%	0.7%	1.9%	10.4%
Panel C: Raw returns over three quarters				
$\Delta\text{BREADTH}_t$	4.403		4.536	2.803
	(4.94)		(4.83)	(3.10)
ΔHOLD_t		0.592	0.154	0.132
		(3.66)	(1.20)	(1.15)

Table 6 (*continued*)

	1. ΔBREADTH$_t$ only	2. ΔHOLD$_t$ only	3. ΔBREADTH$_t$ and ΔHOLD$_t$	4. Additional controls
LOGSIZE$_t$				0.007
				(1.04)
BK/MKT$_t$				0.022
				(2.38)
MOM12$_t$				0.076
				(4.35)
XTURNOVER$_t$				−0.109
				(3.09)
No. of quarters	79	79	79	79
Average R^2	1.2%	0.8%	1.9%	10.1%
Panel D: Raw returns over four quarters				
ΔBREADTH$_t$	4.469		4.504	2.932
	(3.51)		(3.77)	(3.18)
ΔHOLD$_t$		0.722	0.207	0.145
		(3.25)	(1.13)	(0.95)
LOGSIZE$_t$				0.013
				(1.64)
BK/MKT$_t$				0.029
				(2.60)
MOM12$_t$				0.084
				(4.16)
XTURNOVER$_t$				−0.141
				(3.10)
No. of quarters	79	79	79	79
Average R^2	1.2%	0.9%	1.9%	9.9%

regression, a two-standard deviation spread in ΔBREADTH generates a differential in expected returns of 2.71% over a four-quarter horizon.

To put the forecasting power of ΔBREADTH in perspective, consider the coefficient estimate of 0.029 for the BK/MKT variable in the same column-four regression in Panel D of Table 6. This estimate implies that a two-standard deviation spread in BK/MKT generates a differential in expected returns of 3.33% over a four-quarter horizon. Thus when put on equal footing, it appears that ΔBREADTH and BK/MKT have roughly similar incremental forecasting power over a one-year horizon.

5.3. Robustness checks

We have conducted a range of further tests to verify the robustness of our basic results. Table 7 begins with the full-set-of-controls four-quarter Fama-MacBeth specification in column 4 of Table 6 Panel D (which, for ease of comparability, is also reproduced as column 1 of Table 7) and then displays several of the more significant variations explored.

Table 7

Forecasting returns with ΔBREADTH: four-quarter Fama-MacBeth robustness checks

The sample includes stocks from the NYSE, AMEX, and NASDAQ between 1979 and 1998 (1979–1997 for column 5) with a market capitalization above the 20th percentile using NYSE breakpoints. The dependent variables are raw returns over four quarters. $\Delta\text{BREADTH}_t$ is the change in the breadth of ownership for a stock in quarter t. IN_t is the fraction of mutual funds in the sample at both quarters $t-1$ and t that have established a new position in a stock at quarter t. OUT_t is the fraction of mutual funds that have completely removed an existing position in a stock at quarter t. ΔHOLD_t is the change in aggregate mutual fund holdings of a stock in quarter t. LOGSIZE_t is the log of market capitalization at the end of quarter t. BK/MKT_t is the most recently available observation of book-to-market ratio at the end of quarter t. MOM12 is the raw return from the beginning of quarter $t-3$ to the end of quarter t. MOM3 is the raw return from the beginning of quarter t to the end of quarter t. Column 2 uses MOM12 lagged one month. XTURNOVER_t is share turnover demeaned within each quarter by the average turnover for the firm's exchange (either NYSE/AMEX or NASDAQ). t-statistics, which are in parentheses, are adjusted for serial correlation and heteroskedasticity.

	1. Base-case	2. Momentum with one-month lag	3. Momentum decomposed	4. ΔBREADTH decomposed	5. With future ΔHOLD
$\Delta\text{BREADTH}_t$	2.932	2.486	2.390		2.336
	(3.18)	(2.29)	(2.36)		(2.10)
IN_t				3.674	
				(1.83)	
OUT_t				−2.008	
				(1.43)	
ΔHOLD_t	0.145	0.090	0.075	0.134	0.236
	(0.95)	(0.57)	(0.44)	(0.87)	(1.43)
ΔHOLD_{t+2}					1.832
					(6.37)
ΔHOLD_{t+1}					2.342
					(7.76)
ΔHOLD_{t+3}					2.274
					(8.05)
ΔHOLD_{t+4}					1.980
					(6.67)
LOGSIZE_t	0.013	0.019	0.002	0.013	0.007
	(1.64)	(2.54)	(0.31)	(1.41)	(0.96)
BK/MKT_t	0.029	0.030	0.022	0.028	0.027
	(2.60)	(2.49)	(1.93)	(2.39)	(2.70)
MOM12_t (MOM3_t	0.084	0.083	0.149	0.086	0.097
in column 3)	(4.16)	(4.61)	(4.66)	(4.50)	(4.68)
MOM3_{t-1}			0.141		
			(5.10)		
MOM3_{t-2}			0.075		
			(2.82)		
MOM3_{t-3}			0.016		
			(0.58)		
XTURNOVER_t	−0.141	−0.126	−0.128	−0.138	−0.133
	(3.10)	(2.57)	(2.92)	(2.50)	(3.00)
No. of Quarters	79	79	79	79	75
Average R^2	9.9%	10.1%	13.4%	10.8%	18.1%

5.3.1. Alternative momentum controls

Given the pronounced correlation between ΔBREADTH and MOM12, it makes sense to ask whether our results are sensitive to different specifications of the momentum control. In column 2 of Table 7, the MOM12 variable is redefined so that it is lagged one month. Jegadeesh and Titman (1993) and others have argued that this approach can potentially improve the measurement of momentum effects, by eliminating microstructure-related noise. This variation reduces the coefficient on ΔBREADTH by about 15%, from 2.93 to 2.49, but leaves it still statistically significant.

In a similar spirit, column 3 of Table 7 decomposes MOM12 into four separate terms, each covering three months' worth of past returns. This less parsimonious representation of momentum simply allows the past-return terms to soak up more of the explanatory power for future returns. The effect here is close to that in the previous column, with the coefficient on ΔBREADTH falling to 2.39, but again remaining statistically significant.

5.3.2. Decomposing the predictive power of ΔBREADTH: IN vs. OUT

Our theoretical model implies that both components of ΔBREADTH (IN and OUT) should play a role in helping to forecast returns. In other words, both high values of IN as well as low values of OUT should predict higher future returns. Thus it would be somewhat awkward for the model if, for example, IN was contributing strongly to the predictive power of ΔBREADTH by attracting a large positive coefficient, while OUT was partially nullifying this contribution by also attracting a positive, albeit smaller, coefficient.

We investigate this possibility in column 4 of Table 7, replacing ΔBREADTH with IN and OUT and allowing for a separate coefficient on each. Both coefficients are economically substantial and of the predicted signs (3.67 for IN and –2.01 for OUT). Yet, when we separate them this way, we barely have the precision to say that either is statistically significant in its own right and cannot conduct a meaningful test of whether the two are reliably different from one another—the t-stats are only 1.83 and 1.43 for IN and OUT, respectively.

5.3.3. Is ΔBREADTH just forecasting future mutual fund demand?

Another concern is that the ΔBREADTH variable forecasts future returns not because of the theoretical effect that we are interested in, but rather because it predicts future mutual fund demand. In particular, one might hypothesize that if a mutual fund first establishes a long position in a stock in quarter t—thereby registering an increase in $\Delta BREADTH_t$—this fund might be particularly likely to continue buying shares in quarters t+1, t+2, etc. If this is true, and if these further rounds of buying push the price up in subsequent quarters via a price-pressure effect, this could lead to the sorts of results that we have documented.

As a naïve attempt to control for this price-pressure hypothesis, we include in column 5 of Table 7 future values of ΔHOLD (i.e., future mutual fund net purchases) as additional independent variables in the Fama-MacBeth regression. Specifically, we re-run the regression, adding the realizations of ΔHOLD over the next four quarters (i.e., $\Delta HOLD_{t+1}$, $\Delta HOLD_{t+2}$, $\Delta HOLD_{t+3}$, and $\Delta HOLD_{t+4}$). This approach is conservative, since there is strong reason to suspect a reverse-causality effect that biases the coefficients on the future ΔHOLD terms up, and hence, if $\Delta BREADTH_t$ is in fact positively correlated with these future ΔHOLD terms, biases the coefficient on $\Delta BREADTH_t$ toward zero. The potential for bias arises because ΔHOLD would likely be positively correlated with contemporaneous returns even in the absence of any price-pressure effect, simply because mutual funds are known to be trend-chasers—i.e., because mutual fund purchases respond to price movements, rather than vice versa.[8]

In spite of this potential for downward bias and the fact that the future ΔHOLD terms themselves emerge as strongly significant, the impact on the ΔBREADTH coefficient is only modest. This coefficient falls from its column-1 value of 2.93 to 2.34, a decline of 20%, and remains statistically significant. The conclusion we draw from this (admittedly simplistic) exercise is that it is unlikely that our results are much influenced by price-pressure effects.

Finally, we briefly discuss a couple of further robustness checks which are not displayed in any of the tables.

5.3.4. Seasonality

One might conjecture that movements in ΔBREADTH are more informative at some times of the year than others. For example, it might be that movements in ΔBREADTH in the fourth quarter are disproportionately influenced by institutional factors outside of our theoretical model, such as year-end tax-loss-selling and window-dressing. If this is true, portfolios formed based on fourth-quarter values of ΔBREADTH might be expected to be less profitable than those formed in other quarters.

To investigate this possibility, we disaggregate the analysis in Table 4 by the quarter of portfolio formation. That is, we calculate (P10−P1) profits separately for ΔBREADTH portfolios formed in the first quarter, the second quarter, the third quarter, and the fourth quarter. Overall, this disaggregation effort does not turn up much in the way of differences across quarters. For example, using raw returns and an investment horizon of four quarters, the (P10−P1) spreads are 6.76%, 6.08%, 6.49%, and 6.37% for portfolios formed at the end of the first, second, third, and fourth quarters respectively.

5.3.5. Outliers

As a last check, we truncate all stock-return observations to their three-standard-deviation values (these thresholds are calculated separately within each size class every quarter) and then redo everything in Tables 4 and 6. As it turns out, all the results remain virtually unchanged, suggesting that none of our inferences are driven by large outliers.

[8] Grinblatt et al. (1995) document the trend-chasing tendencies of mutual funds.

6. Conclusions

We draw two basic conclusions from the work reported here. First, the evidence is broadly consistent with the idea that short-sales constraints matter for equilibrium stock prices and expected returns.[9] As predicted by our model, stocks experiencing declines in breadth of ownership—a proxy for short-sales constraints becoming more tightly binding—subsequently underperform those for which breadth has increased. Second, of the variables already known to forecast returns such as book-to-market, earnings-to-price, and momentum, it appears that the momentum phenomenon is the one most closely bound up with short-sales constraints. In this regard, our findings tie in nicely with previous research (e.g., Hong et al., 2000) which has hinted at the same conclusion.

An interesting question that our work raises, but does not answer, is this: *why* do short-sales constraints seem to be so strongly binding? Or said slightly differently: why, in spite of the high apparent risk-adjusted returns to strategies involving shorting, is there so little aggregate short interest in virtually all stocks? Recent evidence suggests that the direct transactions costs of going short (manifested as the fee paid to a borrow a stock for shorting) can be a significant impediment in a small fraction of cases (D'Avolio, 2002; Geczy et al., 2002; and Jones and Lamont, 2002). Yet, we are skeptical that all, or even most of the answer has to do with these specific transactions costs. With respect to the mutual funds that we have been studying, there is a facile alternative answer, namely that they are simply prohibited by their charters from ever taking short positions. But why are such restrictions so pervasive? And why do we not see individuals or other types of institutions filling the void? At this point, we do not really know.

Appendix A

A.1. Solving for the equilibrium price with short-sales constraints

After evaluating the integral in Eq. (3), the aggregate demand of the buyers and the arbitrageurs is given by

$$Q^{\mathrm{DC}} = \frac{\gamma_B(F + H - P)^2}{4H} + \gamma_A(F - P). \tag{A.1}$$

[9] After completing the first draft of this paper, we became aware of independently developed work by Diether, Malloy and Scherbina (2002), who also seek to test Miller's (1977) ideas. In their case, however, they proceed by trying to measure differences of opinion (corresponding to the parameter H in our model) directly. To do so, they computes the standard deviation of analysts' earnings forecasts (scaled by the mean earnings forecast). Consistent with Miller (1977), they then find that a portfolio that is long low-analyst-dispersion stocks and short high-analyst-dispersion stocks yields significant positive returns.

Setting $Q^{DC} = Q$ gives a market-clearing condition that is a quadratic function in P. Applying the quadratic formula yields two roots given by

$$P = F + H + \frac{2H}{\gamma_B}\left(\gamma_A \pm \sqrt{\gamma_A^2 + \gamma_A\gamma_B + \gamma_B\frac{Q}{H}}\right). \tag{A.2}$$

The larger of the two roots can never be an equilibrium price since it exceeds the highest possible valuation of the short-sales constrained investors, $F + H$. Hence, taking the smaller of the two roots gives the constrained price P^C in Eq. (4).

Next, note that P^C is the equilibrium price only when the short-sales constraint is actually binding, which requires that $H \geqslant Q/(\gamma_A + \gamma_B)$. In fact, it is easy to verify that

$$P^c|_{H=Q/(\gamma_A+\gamma_B)} = F - \frac{Q}{\gamma_A + \gamma_B}, \tag{A.3}$$

and so $P^C = P^U$ at $H = Q/(\gamma_A + \gamma_B)$ at which point the buyers with the lowest valuation of $F - H$ are just at their reservation value. When $H < Q/(\gamma_A + \gamma_B)$, the market clears at the equilibrium price of $P^U$and even buyers with the lowest valuation of $F - H$ are long the stock. That is, when the degree of divergence of opinion is less than the risk-tolerance-adjusted supply of the stock, short-sales constraints do not bind and the equilibrium price is simply that of the unconstrained case.

For simplicity of exposition throughout Appendix A, we make the following two definitions. First, we define the following constant:

$$\lambda = \gamma_A^2 + \gamma_A\gamma_B + \gamma_B\frac{Q}{H}. \tag{A.4}$$

Next, we rewrite the breadth of ownership B given in Eq. (5) as

$$B = \text{Min}\left[\frac{F + H - P^*}{2H}, 1\right] = \text{Min}\left[\frac{\sqrt{\lambda} - \gamma_A}{\gamma_B}, 1\right]. \tag{A.5}$$

A.2. Proof that P^* is increasing in H

To show that P^* is increasing in H, we first establish a few additional properties of P^C. Taking the derivative of P^C with respect to H, we have

$$\frac{\partial P^C}{\partial H} = 1 + \frac{2}{\gamma_B}\left(\gamma_A - \sqrt{\lambda}\right) + \frac{Q}{H}\lambda^{-1/2}. \tag{A.6}$$

Evaluating this derivative at $H = Q/(\gamma_A + \gamma_B)$, we have

$$\left.\frac{\partial P^C}{\partial H}\right|_{H=Q/(\gamma_A+\gamma_B)} = 0. \tag{A.7}$$

Next, taking the second derivative of P^C with respect to H, it is easy to show that this second derivative is nonnegative:

$$\frac{\partial^2 P}{\partial H^2} = \frac{Q^2\gamma_B}{2H^3}\lambda^{-3/2} \geqslant 0. \tag{A.8}$$

Recall that the equilibrium stock price for $H < Q/(\gamma_A + \gamma_B)$ is simply P^{U}. Then for $H \geqslant Q/(\gamma_A + \gamma_B)$, the properties of P^{C} given by Eqs. (A.3), (A.7), and (A.8) imply that P^{C} increases monotonically upward from P^{U} with H. We conclude that for all H, the stock price is upward biased relative to the frictionless benchmark and this upward bias increases (weakly) in H.

A.3. Relationship between price and arbitrageurs' risk tolerance

Taking the derivative of P^{C} with respect to γ_A, we have

$$\frac{\partial P^C}{\partial \gamma_A} = \frac{2H}{\gamma_B}\left(1 - \frac{2\gamma_A + \gamma_B}{2\sqrt{\lambda}}\right). \tag{A.9}$$

Observe that the sign of this derivative is negative if and only if

$$2\sqrt{\lambda} \leqslant 2\gamma_A + \gamma_B. \tag{A.10}$$

With some algebra, it is easy to show that this condition is equivalent to

$$H \geqslant \frac{4Q}{\gamma_B}. \tag{A.11}$$

A.4. Proof of Proposition 1

We have already shown that the price P^* is increasing in H, and hence the expected return $(F - P^*)$ is decreasing in H. Moreover, we know that all buyers are long the stock when $H < Q/(\gamma_A + \gamma_B)$, whereas not all buyers will be long the stock when $H \geqslant Q/(\gamma_A + \gamma_B)$. Finally, once inside the constrained region where $H \geqslant Q/(\gamma_A + \gamma_B)$, it follows from Eq. (A.5) that breadth of ownership decreases with H since λ decreases in H. Thus breadth is decreasing in H overall, which establishes the proposition.

A.5. Proof of Proposition 2

This follows immediately from the formula for B in Eq. (6) of the text. Holding fixed H, B is monotonically increasing in the expected return $(F - P^*)$.

A.6. Proof of Proposition 3

This follows from the result established above, namely that the derivative of P^{C} with respect to γ_A is negative for $H \geqslant (4Q/\gamma_B)$.

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