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ABSTRACT

We develop a model of stock prices in which there are both differences of opinion among investors as well as short-sales constraints. The key insight that emerges is that breadth of ownership is a valuation indicator. When breadth is low—i.e., when few investors have long positions in the stock—this signals that the short-sales constraint is binding tightly, implying that prices are high relative to fundamentals and that expected returns are therefore low. Thus reductions (increases) in breadth should forecast lower (higher) returns. Using quarterly data on mutual fund holdings over the period 1979-1998, we find evidence supportive of this prediction: 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 6.38% in the first twelve months after portfolio formation. After adjusting for size, book-to-market and momentum, the corresponding figure is 4.95%.

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I. 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 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.[1] 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. 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 will be the price of a stock in equilibrium, and hence the lower will be subsequent returns.

This theory would seem to be very appealing, not only because of its simplicity, but also because both of 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.[2]

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 clearly seems to be met at the individual-stock level, even apart from any transactions costs

[1] See, e.g., Harrison and Kreps (1978), Jarrow (1980), Diamond and Verrecchia (1987), Allen, Morris and Postlewaite (1993), Morris (1996) and Hong and Stein (1999) for other theoretical work on the implications of short-sales constraints for stock prices.
[2] Important work on differences of opinion and trading volume includes Varian (1989), Harris and Raviv (1993), Kandel and Pearson (1995), and Odean (1998).

associated with shorting, since many important institutional investors, such as mutual funds, are simply prohibited by their charters from ever taking short positions.[3] Indeed, aggregate short interest is very low for the vast majority of stocks. Dechow et al (2000) document that, over the period 1976-1993, more than 80% of NYSE/AMEX firms had short interest of less than 0.5% of shares oustanding; 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 twenty-five 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 from the market price." (Figlewski and Webb (1993), p. 762). Among the other papers that have attempted to forecast returns with short interest are Brent, Morse and Stice (1990), Figlewski and Webb (1993), Woolridge and Dickinson (1994), Asquith and Meulbroek (1995) and Dechow et al (2000).

However, this approach has a couple of important limitations. First, as noted above, the overwhelming 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 very small, thereby potentially reducing the power of any tests, as well as calling into question the generalizability of the results. Second,

[3] Brown, Carlson and Chapman (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.

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 very fragile ground. For example, suppose that variation across stocks in short interest reflects either variation in the transactions costs of shorting, or equivalently, variation in the number of sophisticated arbitrageurs who can cost-effectively put on short trades.[4] If so, a stock with a very low or zero value of short interest may simply be one that is difficult 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 (increases) in breadth should forecast lower (higher) subsequent 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 that as a result also forecast increased risk-adjusted returns. Possible

[4] In fact, Dechow et al. (2000) show that short interest is lower in stocks for which the transactions costs of shorting are high.

candidates include book-to-market, (Fama and French (1992), Lakonishok, Shleifer and Vishny (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 twelve 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, as well as to 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 twelve months.

The mutual fund data is extremely useful for our purposes, because it represents 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 literally sitting on the sidelines, i.e., having no position at all.

Nevertheless, 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 does 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 100 shares of stock outstanding and 100 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, Jegadeesh and Wermers (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.

Fortunately, we can control for the effect identified by Chen, Jegadeesh and Wermers. For example, in the context of a regression that uses our change-in-breadth variable to forecast returns, we can add as a control their changes-in-aggregate-fund-holdings variable. This ensures that the breadth measure picks 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.

The remainder of the paper is organized as follows. In Section II, we build 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. In Section III, we describe the data we use to conduct these tests. Our main empirical results are in Sections IV and V. Section VI concludes.

II. The Model

A. Basic Setup

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 $Max[0, \gamma_B(V_i - P)]$.

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 likely to be 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:

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

Performing the integration indicated in equation (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:

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

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:

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

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

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

Note, 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 $H \geq \frac{Q}{\gamma_A + \gamma_B}$. Thus overall, the equilibrium price, which we denote by P^*, is given by:

$$P^* = \begin{cases} P^U \;\; if \;\; H < \dfrac{Q}{\gamma_A + \gamma_B} \\ P^C \;\; if \;\; H \geq \dfrac{Q}{\gamma_A + \gamma_B} \end{cases} \tag{5}$$

The equilibrium price P^* has a variety of intuitive properties, which we establish formally in the appendix. Most notably, 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, $\left(F - P^*\right)$, 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.[5]

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 $H \geq \frac{4Q}{\gamma_B}$), 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.

B. 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

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[5] We are using "expected return" 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.

to short-sales constraints—i.e., the buyers. We define breadth of ownership B as the fraction of buyers who are long the stock:

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

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 the appendix, 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, and these stocks 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 the appendix, 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 equation (6). Holding fixed H, breadth is determined completely by $\left(F - P^*\right)$—i.e., by the difference between fundamentals and price, or equivalently, by the expected return on the stock. Thus anything whatsoever 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.[6] 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 the appendix, we prove:

Proposition 3: Suppose $H \geq \frac{4Q}{\gamma_B}$*. In this case,* $P^* \geq F$ *so that arbitrageurs take short positions. Moreover, an increase in* γ_A *leads to an increase in short interest. This increase in*

[6] One can think of changes in Q as not literally supply shocks, but rather as unmodelled exogenous changes in investor sentiment—as in DeLong et al (1990)—that induce divergences between prices and fundamentals.

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—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.

C. 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 (e.g., book-to-market, earnings-to-price, 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 $\left(F - P^*\right)$ on the stock.[7] 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, he 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.

[7] Again, $(F - P^*)$ measures net risk-adjusted expected returns in the sense that in a classical factor-risk model, we would always have $(F - P^*) = 0$. See footnote 5 above.

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.

III. Data

A. Construction of Variables

Our data on mutual fund holdings comes 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.[8] 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

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

activities of existing funds rather than changes in the composition of the universe.[9] Thus to define the change in breadth of ownership, denoted as $\Delta BREADTH_t$, 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*.

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 $\Delta HOLD_t$ 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, Jegadeesh and Wermers (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.[10] $LOGSIZE_t$ 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 recent fiscal year-end. For each

[9] At the beginning of our sample, first quarter of 1979, we have data on 582 mutual funds. At the end of our sample, the fourth quarter of 1998, we have data on 8950 mutual funds.
[10] These stocks are identified by a CRSP share type code of 10 or 11.

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 $MOM12_t$.

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 $TURNOVER_t$. 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 $XTURNOVER_t$.[11]

B. 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 mutual funds are essentially non-players in the very smallest stocks—those in the bottom size quintile (based on NYSE breakpoints). The mean value of $BREADTH_t$ is much smaller than in the other size classes, as is the standard deviation of $\Delta BREADTH_t$. Given this lack of action in our key right-hand-side variable, in the tests that follow we eliminate the bottom-quintile stocks from our sample, and focus only on those stocks with market capitalization above the 20th percentile NYSE breakpoint.

Panels B and C make it clear that we cannot simply use the raw value of $BREADTH_t$ as an empirical analog to our model's *B* variable. In levels, $BREADTH_t$ is effectively a permanent

[11] In a regression context, using the XTURNOVER variable is equivalent to using unadjusted turnover, plus turnover interacted with a NASDAQ dummy.

firm characteristic, with a quarterly autocorrelation of 0.99. Not surprisingly, $BREADTH_t$ is highly correlated with $LOGSIZE_t$ (contemporaneous correlation = 0.69), as well as with $XTURNOVER_t$ (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 $BREADTH_t$ and BK/MKT_t is –0.062.

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

IV. Determinants of ΔBREADTH

In Table 2, we investigate the determinants of $\Delta BREADTH_t$. We have two goals in doing so. First, as noted in the introduction, we need to be aware of any correlation between $\Delta BREADTH_t$ and the Chen-Jegadeesh-Wermers variable $\Delta HOLD_t$; 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 $\Delta BREADTH_t$ is capturing the information in other well-known predictors of stock returns.

In Panel A, we present the results of regressing $\Delta BREADTH_t$ against the following five variables: $\Delta HOLD_t$, $LOGSIZE_t$, 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.[12] We then average the regression coefficients across quarters, as in Fama-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 $\Delta BREADTH_t$ 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.[13]

The key conclusions from Panel A of Table 2 are as follows. First, as expected, there is a significant positive correlation between $\Delta BREADTH_t$ and $\Delta HOLD_t$. 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 very strong positive correlation between $\Delta BREADTH_t$ and the momentum variable, $MOM12_t$. Given that momentum is a strong predictor of future returns (Jegadeesh and Titman (1993)), this finding is consistent with Hypothesis 2. Moreover, the finding suggests that *the momentum phenomenon may itself be closely linked 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

[12] Recall that we are dropping the smallest quintile of stocks from our analysis.
[13] This issue becomes even more important when we use $\Delta BREADTH_t$ to forecast returns, and we will take an analogous approach to dealing with it.

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.[14]

On the other hand, Hypothesis 2 strikes out with respect to another well-known return predictor, the book-to-market ratio. The correlation between $\Delta BREADTH_t$ 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 that 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 re-run the same basic exercise, keeping everything the same except replacing BK/MKT_t with the earnings-to-price ratio E/P_t.[15] (The correlation between these

[14] This line of 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, Lim and Stein (2000)).
[15] 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.

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 quite 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 $\Delta BREADTH_t$ 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 by far to be the most closely linked with binding short-sales constraints.

V. Using ΔBREADTH to Forecast Returns

A. Portfolio Sorts

We now turn to Hypotheses 1 and 3, which involve using the ΔBREADTH variable to forecast stock returns. In Tables 3 and 4, this forecasting is done with portfolio sorts. Consider first Panel A of Table 3. 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 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 $\Delta BREADTH_t$ against $\Delta HOLD_t$. 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.[16] As can be seen, the results for raw returns in Panel A of Table 3 are very striking, and are 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 3, we redo everything in Panel A using returns that have been adjusted to control for size and book-to-market. To implement this control, we create portfolio

[16] We have 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.

benchmarks using a characteristics-based procedure similar to Daniel, Grinblatt, Titman, and Wermers (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 sub-quintiles, 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 3 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 3 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 3, 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 4, we disaggregate our Table-3 results by size. Panel A gives a condensed treatment of the raw-returns case, and Panels B and C again 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 3, the results using sorts based on simple ΔBREADTH are very similar.

The general picture that emerges from Table 4 can be summarized as follows. No matter which measure of returns one looks at, predictability based on RESIDUAL ΔBREADTH is stronger among the smaller stocks in quintiles 2 and 3 (especially quintile 3) than among the larger stocks in quintiles 4 and 5. 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 2-5 respectively.

B. Fama-MacBeth Regressions

As an alternative approach to evaluating the forecasting power of ΔBREADTH, we present in Table 5 a series of Fama-MacBeth (1973) regressions. We implement the Fama-MacBeth technique in much the same way as in Table 2. 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 5 then reports the mean coefficients across these 316 regressions, along with the associated t-statistics.[17] 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 5, corresponding to forecast horizons of one, two, three and four quarters. The patterns are very much the same 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.[18] In the second column, the only right-hand-side variable is the Chen-Jegadeesh-Wermers variable, ΔHOLD. Consistent with their findings, ΔHOLD is significant when entered by itself, with a point estimate of 0.7218 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

[17] 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.
[18] From Table 1, Panel A, the standard deviation of ΔBREADTH for quintiles 2-5 is 0.00463. So we have 2 x 4.47 x 0.00463 = 0.0414.

badly damaged by the addition of ΔBREADTH, falling from 0.7218 to 0.2067, and becoming completely statistically insignificant.

Finally, in the fourth column, we add several other control variables to the regression: LOGSIZE, BK/MKT, MOM12 and XTURNOVER.[19] As might be expected from what we have already seen in the portfolio sorts, these added controls—especially the MOM12 variable, which enters very 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.[20] This implies that, controlling for everything else in the 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 0.0293 for the BK/MKT variable in the same column-four regression in Panel D of Table 5. 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 very similar incremental forecasting power. Given the enormous amount of attention that has been lavished on the book-to-market effect, this would seem to constitute a significant victory for our breadth measure.

[19] We include XTURNOVER in our list of controls because a number of recent papers (e.g., Brennan, Chordia and Subrahmanyam (1998)) have found a negative relationship between turnover and expected returns. As can be seen in Table 5, our regressions strongly bear out the existence of this pattern.
[20] If we add the earnings-price ratio E/P as a further control in this regression, it attracts a significantly positive coefficient, and the coefficient on ΔBREADTH is reduced slightly, to 2.58 (t-statistic = 2.96).

C. Robustness Checks

We have conducted a range of further tests to verify the robustness of our basic results. A few of the more significant of these are described below.

1. Is ΔBREADTH just forecasting future mutual-fund demand? One concern is that the ΔBREADTH variable might be forecasting 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 future values of ΔHOLD—i.e., future mutual-fund net purchases—as additional independent variables in the Fama-MacBeth regressions of Table 5. Specifically, we re-run the specification given in column four of Panel D, 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 extremely 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.[21]

In spite of this potential for downward bias, the inclusion of the future ΔHOLD terms has only a modest impact on the ΔBREADTH coefficient. This coefficient, which was 2.93 in the fourth column of Panel D in Table 5, drops to 2.26 (t-statistic = 2.09), a decline of about 23%. The conclusion we draw from this (admittedly simplistic) exercise is that it is unlikely that our results are much influenced by price-pressure effects.

2. 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 3 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.

[21] Grinblatt, Titman and Wermers (1995) document the trend-chasing tendencies of mutual funds.

3. Outliers As a final robustness 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 3 and 5. As it turns out, all the results remain virtually unchanged, suggesting that none of our inferences are driven by large outliers.

VI. 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.[22] 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—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, Lim and Stein (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? We are skeptical that all, or even most of the answer has to do with literal transactions costs of shorting. With respect to the mutual funds that we have been

[22] After completing the first draft of this paper, we became aware of independently developed work by Scherbina (2000), who also seeks to test Miller's (1977) ideas. In her case, however, she proceeds by trying to measure differences of opinion—corresponding to the parameter H in our model—directly. To do so, she computes the standard deviation of analysts' earnings forecasts (scaled by the mean earnings forecast). Consistent with Miller (1977), she then finds that a portfolio that is long low-analyst-dispersion stocks and short high-analyst-dispersion stocks yields significant positive returns.

studying, there is a facile 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 don't really know.

Appendix

Solving for the equilibrium price with short-sales constraints

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

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

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 equation (4).

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

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

and so $P^C = P^U$ at $H = \dfrac{Q}{\gamma_A + \gamma_B}$ at which point the buyers with the lowest valuation of $F - H$ are just at their reservation value. When $H < \dfrac{Q}{\gamma_A + \gamma_B}$, 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 the appendix, 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 equation (5) as

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

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

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

Evaluating this derivative at $H = \dfrac{Q}{\gamma_A + \gamma_B}$, we have

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

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

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

Recall that the equilibrium stock price for $H < \dfrac{Q}{\gamma_A+\gamma_B}$ is simply P^U. Then for $H \geq \dfrac{Q}{\gamma_A+\gamma_B}$, the properties of P^C given by (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.

Relationship between price and arbitrageurs' risk tolerance

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

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

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

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

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

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

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 $H < \frac{Q}{\gamma_A + \gamma_B}$, whereas not all buyers will be long the stock when $H \geq \frac{Q}{\gamma_A + \gamma_B}$. Finally, once inside the constrained region where $H \geq \frac{Q}{\gamma_A + \gamma_B}$, it follows from (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.

Proof of Proposition 2

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

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 $H \geq \frac{4Q}{\gamma_B}$.

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Table 1: Summary Statistics

The sample includes stocks from the NYSE, AMEX and NASDAQ between 1979-1998. $BREADTH_t$ is the fraction of all mutual funds long the stock at the end of quarter t. $\Delta BREADTH_t$ is the change in breadth of ownership from the end of quarter t-1 to quarter t. $HOLD_t$ is the fraction of shares outstanding of a stock held by mutual funds at the end of quarter t. $\Delta HOLD_t$ 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	0.0129	0.0230	0.0709	0.0256	0.0143	0.0076	0.0025
Standard Dev.	0.0246	0.0312	0.0510	0.0142	0.0093	0.0055	0.0025
$\Delta BREADTH_t$							
Mean	-0.000048	-0.000032	-0.000154	-0.000071	0.000020	0.000004	-0.000066
Standard Dev.	0.003386	0.004633	0.009092	0.004620	0.003061	0.002012	0.000958
$HOLD_t$							
Mean	0.0858	0.1090	0.1080	0.1233	0.1139	0.0988	0.0619
Standard Dev.	0.0862	0.0926	0.0837	0.0996	0.0980	0.0873	0.0717
$\Delta HOLD_t$							
Mean	0.0012	0.0019	0.0016	0.0016	0.0022	0.0019	0.0005
Standard Dev.	0.0289	0.0255	0.0163	0.0238	0.0261	0.0290	0.0320
$LOGSIZE_t$							
Mean	5.0489	6.4235	8.5782	7.1687	6.2058	5.2949	3.6381
Standard Dev.	1.8182	1.3409	0.9985	0.6115	0.5654	0.5676	0.9608
BK/MKT_t							
Mean	0.7216	0.6643	0.6196	0.6578	0.6485	0.6972	0.7804
Standard Dev.	2.2380	0.5677	0.4629	0.4874	0.5020	0.6752	3.1324
E/P_t							
Mean	-0.1936	0.0379	0.0677	0.0581	0.0433	0.0052	-0.4106
Standard Dev.	0.9538	0.1268	0.0522	0.0737	0.1068	0.2000	1.5114
NYSE/AMEX $TURNOVER_t$							
Mean	0.1582	0.1757	0.1773	0.1884	0.1765	0.1629	0.1237
Standard Dev.	0.1573	0.1628	0.1375	0.1621	0.1742	0.1718	0.1397
NASDAQ $TURNOVER_t$							
Mean	0.2976	0.3754	0.4402	0.4277	0.3938	0.3474	0.2521
Standard Dev.	0.3559	0.4292	0.4802	0.4949	0.4554	0.3890	0.2955
$MOM12_t$							
Mean	0.2015	0.2425	0.2400	0.2353	0.2423	0.2476	0.1573
Standard Dev.	0.6288	0.5170	0.3622	0.4416	0.5067	0.6111	0.7276
No. of Obs.	204829	103747	16740	19927	27216	39864	101082

Panel B: Contemporaneous Correlations (Using only firms above 20th percentile in size)

	$BREADTH_t$	$\Delta BREADTH_t$	$HOLD_t$	$\Delta HOLD_t$	$LOGSIZE_t$	BK/MKT_t	E/P_t	$XTURNOVER_t$	$MOM12_t$
$BREADTH_t$		0.056	0.080	0.010	0.691	-0.062	0.084	0.090	-0.011
$\Delta BREADTH_t$			0.026	0.185	0.014	-0.025	0.014	0.002	0.169
$HOLD_t$				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)

	$BREADTH_{t-1}$	$\Delta BREADTH_{t-1}$	$HOLD_{t-1}$	$\Delta HOLD_{t-1}$	$LOGSIZE_{t-1}$	BK/MKT_{t-1}	E/P_{t-1}	$XTURNOVER_{t-1}$	$MOM12_{t-1}$
$BREADTH_t$	0.9891	0.0606	0.0778	0.0091	0.6974	-0.0634	0.0791	0.0904	-0.0185
$\Delta BREADTH_t$	-0.0920	0.0279	-0.0254	0.0458	-0.0082	-0.0118	0.0189	-0.0094	0.1246
$HOLD_t$	0.0761	0.0381	0.9619	0.1677	0.2288	-0.2062	-0.0329	0.2859	0.0899
$\Delta HOLD_t$	-0.0161	0.0282	-0.1000	-0.0397	0.0096	-0.0132	0.0183	-0.0200	0.0753
$LOGSIZE_t$	0.6899	0.0187	0.2260	0.0145	0.9880	-0.1537	0.0868	0.0219	0.0162
BK/MKT_t	-0.0604	-0.0407	-0.2007	-0.0339	-0.1641	0.9072	0.1071	-0.0985	-0.1612
E/P_t	0.0741	-0.0026	-0.0365	-0.0013	0.0897	0.1431	0.7983	-0.0794	0.0097
$XTURNOVER_t$	0.0917	0.0237	0.3035	0.0328	0.0332	-0.0993	-0.0883	0.8491	0.1797
$MOM12_t$	-0.0351	0.1465	0.0382	0.1341	0.0031	-0.0492	0.0281	0.1273	0.7114

Table 2: Determinants of ΔBREADTH

The sample includes stocks from the NYSE, AMEX and NASDAQ between 1979-1998 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 coefficients). The coefficients for the full sample are averages of the size sub-sample 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	0.05036	0.00023	-0.00001	0.00080	-0.00007	33.3%	79
	(7.86)	(2.66)	(-0.34)	(13.46)	(-0.41)		
Size Quintile 3	0.07285	0.00046	-0.00005	0.00145	-0.00059	34.8%	79
	(7.80)	(3.75)	(-0.98)	(12.51)	(-2.65)		
Size Quintile 4	0.11640	0.00058	-0.00013	0.00251	-0.00040	33.1%	79
	(7.40)	(2.73)	(-1.22)	(11.45)	(-1.22)		
Size Quintile 5	0.25595	-0.00006	-0.00040	0.00678	-0.00048	32.0%	79
	(7.65)	(-0.20)	(-2.02)	(11.29)	(-0.44)		
Full Sample	0.12389	0.00030	-0.00015	0.00289	-0.00039	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	0.05033	0.00023	0.00025	0.00079	-0.00003	34.8%	79
	(7.86)	(2.64)	(2.74)	(12.88)	(-0.15)		
Size Quintile 3	0.07294	0.00045	0.00048	0.00145	-0.00055	33.1%	79
	(7.79)	(3.64)	(2.94)	(12.41)	(-2.44)		
Size Quintile 4	0.11591	0.00057	0.00109	0.00252	-0.00034	31.8%	79
	(7.42)	(2.74)	(2.73)	(11.41)	(-0.91)		
Size Quintile 5	0.25752	-0.00005	0.00176	0.00678	-0.00045	32.9%	79
	(7.68)	(-0.16)	(1.69)	(11.73)	(-0.42)		
Full Sample	0.12417	0.0003	0.00089	0.00289	-0.00034	33.2%	79
	(7.98)	(2.07)	(3.25)	(13.33)	(-0.99)		

Table 3: Returns to Portfolio Strategies Based on ΔBREADTH

The sample includes stocks from NYSE/AMEX and NASDAQ between 1979-1998 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 4 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 4 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-stats, which are in parentheses, are adjusted for serial-correlations using a Newey-West estimator with lags of up to 4 quarters.

Panel A: Raw Returns

	Sort on ΔBREADTH				Sort on Residual ΔBREADTH			
Cumulative Returns After:	1 Quarter	2 Quarters	3 Quarters	4 Quarters	1 Quarter	2 Quarters	3 Quarters	4 Quarters
Decile 1	0.0293	0.0583	0.0927	0.1348	0.0299	0.0603	0.0953	0.1407
	(3.07)	(3.49)	(3.94)	(4.47)	(3.08)	(3.56)	(4.03)	(4.60)
2	0.0335	0.0719	0.1150	0.1652	0.0384	0.0787	0.1196	0.1665
	(3.44)	(4.18)	(4.78)	(5.27)	(4.04)	(4.54)	(4.96)	(5.47)
3	0.0380	0.0802	0.1204	0.1641	0.0364	0.0804	0.1255	0.1745
	(4.27)	(4.83)	(5.10)	(5.60)	(3.99)	(4.85)	(5.17)	(5.77)
4	0.0411	0.0856	0.1280	0.1769	0.0389	0.0829	0.1279	0.1769
	(4.83)	(5.30)	(5.44)	(5.93)	(4.61)	(5.28)	(5.47)	(5.95)
5	0.0365	0.0804	0.1267	0.1795	0.0391	0.0821	0.1239	0.1755
	(4.43)	(5.00)	(5.46)	(6.04)	(4.38)	(4.94)	(5.29)	(5.83)
6	0.0410	0.0841	0.1290	0.1794	0.0385	0.0825	0.1284	0.1749
	(4.42)	(4.86)	(5.15)	(5.76)	(4.53)	(5.05)	(5.44)	(6.11)
7	0.0383	0.0821	0.1253	0.1729	0.0403	0.0833	0.1262	0.1713
	(4.35)	(4.99)	(5.32)	(5.79)	(4.47)	(4.88)	(5.34)	(5.71)
8	0.0445	0.0908	0.1363	0.1833	0.0412	0.0842	0.1308	0.1788
	(4.56)	(4.98)	(5.49)	(5.93)	(4.28)	(4.61)	(5.11)	(5.51)
9	0.0439	0.0889	0.1376	0.1857	0.0434	0.0872	0.1327	0.1800
	(4.57)	(4.76)	(5.16)	(5.70)	(4.74)	(4.73)	(5.17)	(5.65)
10	0.0495	0.0966	0.1478	0.1986	0.0494	0.0980	0.1496	0.2032
	(4.47)	(4.68)	(5.04)	(5.33)	(4.43)	(4.85)	(5.17)	(5.54)
P10-P1	0.0202	0.0382	0.0551	0.0638	0.0196	0.0377	0.0543	0.0625
	(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

Cumulative Returns After:	Sort on ∆BREADTH 1 Quarter	2 Quarters	3 Quarters	4 Quarters	Sort on Residual ∆BREADTH 1 Quarter	2 Quarters	3 Quarters	4 Quarters
Decile 1	-0.0099	-0.0224	-0.0303	-0.0352	-0.0095	-0.0208	-0.0286	-0.0304
	(-4.40)	(-6.10)	(-5.21)	(-4.35)	(-4.49)	(-6.02)	(-6.12)	(-4.72)
2	-0.0061	-0.0103	-0.0113	-0.0102	-0.0013	-0.0035	-0.0062	-0.0079
	(-3.82)	(-4.30)	(-4.29)	(-2.49)	(-0.80)	(-1.13)	(-1.60)	(-1.89)
3	-0.0012	-0.0013	-0.0060	-0.0099	-0.0032	-0.0020	-0.0017	-0.0014
	(-0.91)	(-0.45)	(-1.48)	(-1.88)	(-2.28)	(-0.77)	(-0.58)	(-0.33)
4	-0.0002	0.0010	-0.0014	-0.0007	-0.0012	-0.0004	0.0001	0.0008
	(-0.13)	(0.33)	(-0.44)	(-0.17)	(-0.60)	(-0.13)	(0.02)	(0.29)
5	-0.0021	-0.0024	-0.0008	0.0015	-0.0007	-0.0005	-0.0035	-0.0006
	(-1.44)	(-0.95)	(-0.23)	(0.29)	(-0.39)	(-0.18)	(-1.01)	(-0.12)
6	-0.0002	0.0013	0.0021	0.0043	-0.0008	0.0005	0.0022	-0.0009
	(-0.11)	(0.39)	(0.46)	(0.91)	(-0.40)	(0.17)	(0.55)	(-0.17)
7	-0.0003	-0.0006	-0.0018	-0.0025	0.0003	0.0002	-0.0016	-0.0039
	(-0.17)	(-0.23)	(-0.48)	(-0.45)	(0.17)	(0.09)	(-0.55)	(-1.02)
8	0.0053	0.0099	0.0109	0.0097	0.0019	0.0024	0.0046	0.0049
	(2.82)	(3.38)	(3.08)	(2.51)	(1.09)	(0.86)	(1.31)	(1.44)
9	0.0041	0.0075	0.0119	0.0128	0.0041	0.0065	0.0085	0.0075
	(2.30)	(2.24)	(2.51)	(2.57)	(3.04)	(2.10)	(2.21)	(1.92)
10	0.0105	0.0165	0.0256	0.0287	0.0101	0.0175	0.0261	0.0319
	(3.08)	(2.65)	(2.85)	(2.62)	(2.87)	(3.00)	(3.26)	(3.13)
P10-P1	0.0204	0.0389	0.0559	0.0639	0.0196	0.0383	0.0547	0.0624
	(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

Cumulative Returns After:	Sort on ΔBREADTH 1 Quarter	2 Quarters	3 Quarters	4 Quarters	Sort on Residual ΔBREADTH 1 Quarter	2 Quarters	3 Quarters	4 Quarters
Decile 1	-0.0057	-0.0166	-0.0231	-0.0262	-0.0055	-0.0148	-0.0219	-0.0221
	(-2.73)	(-5.02)	(-4.51)	(-3.77)	(-2.82)	(-4.70)	(-5.29)	(-3.90)
2	-0.0049	-0.0076	-0.0079	-0.0062	-0.0003	-0.0020	-0.0036	-0.0060
	(-3.19)	(-3.51)	(-3.60)	(-1.92)	(-0.21)	(-0.68)	(-1.01)	(-1.65)
3	-0.0005	-0.0007	-0.0063	-0.0093	-0.0022	-0.0007	-0.0001	0.0011
	(-0.47)	(-0.28)	(-1.77)	(-2.02)	(-1.63)	(-0.30)	(-0.02)	(0.29)
4	0.0004	0.0027	0.0007	0.0017	0.0003	0.0015	0.0014	0.0032
	(0.25)	(1.05)	(0.29)	(0.47)	(0.20)	(0.65)	(0.55)	(1.14)
5	-0.0023	-0.0034	-0.0022	0.0006	-0.0013	-0.0020	-0.0052	-0.0031
	(-1.90)	(-1.55)	(-0.74)	(0.15)	(-0.89)	(-0.87)	(-1.92)	(-0.87)
6	-0.0001	0.0008	0.0010	0.0025	-0.0009	0.0002	0.0012	-0.0007
	(-0.08)	(0.26)	(0.24)	(0.58)	(-0.52)	(0.07)	(0.31)	(-0.14)
7	-0.0004	-0.0011	-0.0017	-0.0035	-0.0004	-0.0007	-0.0032	-0.0062
	(-0.25)	(-0.42)	(-0.54)	(-0.69)	(-0.25)	(-0.36)	(-1.18)	(-1.94)
8	0.0045	0.0085	0.0089	0.0084	0.0019	0.0011	0.0031	0.0036
	(2.82)	(3.26)	(2.56)	(2.24)	(1.23)	(0.45)	(0.93)	(1.24)
9	0.0017	0.0042	0.0081	0.0078	0.0022	0.0044	0.0067	0.0045
	(0.99)	(1.35)	(1.82)	(1.78)	(1.74)	(1.67)	(1.91)	(1.22)
10	0.0071	0.0126	0.0218	0.0232	0.0062	0.0130	0.0216	0.0258
	(2.50)	(2.39)	(2.92)	(2.54)	(2.02)	(2.53)	(3.21)	(3.06)
P10-P1	0.0128	0.0292	0.0449	0.0495	0.0117	0.0278	0.0435	0.0478
	(3.13)	(4.26)	(4.45)	(3.93)	(2.77)	(4.07)	(4.90)	(4.28)

Table 4: Returns to Portfolio Strategies Based on ΔBREADTH, Disaggregated by Size

The sample includes stocks from NYSE/AMEX and NASDAQ between 1979-1998 with a market capitalization above the 20th percentile using NYSE breakpoints. 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 4 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-stats, which are in parentheses, are adjusted for serial-correlations using a Newey-West estimator with lags of up to 4 quarters.

Panel A: Raw Returns, Sort on Residual ΔBREADTH

	Quintile 2		Quintile 3		Quintile 4		Quintile 5	
Cumulative Returns After:	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters
Decile 1	0.0532	0.1456	0.0540	0.1162	0.0700	0.1529	0.0793	0.1587
	(2.68)	(3.81)	(3.07)	(3.98)	(3.72)	(4.94)	(5.36)	(5.42)
10	0.1046	0.2096	0.0967	0.1986	0.0924	0.2005	0.0949	0.2071
	(4.25)	(4.62)	(4.82)	(5.66)	(4.53)	(5.10)	(4.90)	(6.17)
P10-P1	0.0515	0.0640	0.0427	0.0824	0.0224	0.0476	0.0156	0.0484
	(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

	Quintile 2		Quintile 3		Quintile 4		Quintile 5	
Cumulative Returns After:	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters
Decile 1	-0.0261	-0.0277	-0.0273	-0.0506	-0.0113	-0.0206	-0.0076	-0.0179
	(-5.72)	(-2.47)	(-4.08)	(-5.40)	(-1.50)	(-2.08)	(-1.36)	(-1.96)
10	0.0252	0.0350	0.0153	0.0310	0.0140	0.0323	0.0090	0.0283
	(3.34)	(2.87)	(2.16)	(2.41)	(1.57)	(1.94)	(1.25)	(2.79)
P10-P1	0.0513	0.0627	0.0426	0.0815	0.0253	0.0528	0.0166	0.0462
	(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

	Quintile 2		Quintile 3		Quintile 4		Quintile 5	
Cumulative Returns After:	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters	2 Quarters	4 Quarters
Decile 1	-0.0196	-0.0201	-0.0190	-0.0379	-0.0062	-0.0120	-0.0053	-0.0144
	(-5.16)	(-2.00)	(-2.88)	(-4.20)	(-0.88)	(-1.23)	(-0.94)	(-1.61)
10	0.0201	0.0300	0.0117	0.0244	0.0106	0.0263	0.0028	0.0189
	(2.87)	(2.81)	(1.85)	(2.21)	(1.48)	(1.89)	(0.49)	(2.33)
P10-P1	0.0397	0.0502	0.0307	0.0623	0.0168	0.0382	0.0080	0.0333
	(5.03)	(3.14)	(2.86)	(4.43)	(1.95)	(2.44)	(0.87)	(2.66)

Table 5: Forecasting Returns with ΔBREADTH: Fama-MacBeth Regressions

The sample includes stocks from the NYSE, AMEX and NASDAQ between 1979-1998 with a market capitalization above the 20th percentile using NYSE breakpoints. The dependent variables are raw returns over 1 to 4 quarters. $\Delta BREADTH_t$ is 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. 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.

Panel A: Raw Returns over 1 Quarter

	1. $\Delta BREADTH_t$ Only	2. $\Delta HOLD_t$ Only	3. $\Delta BREADTH_t$ and $\Delta HOLD_t$	4. Additional Controls
$\Delta BREADTH_t$	2.0453		2.0550	1.1873
	(3.72)		(3.49)	(2.67)
$\Delta HOLD_t$		0.2571	0.0931	0.0719
		(2.90)	(1.25)	(1.17)
$LOGSIZE_t$				-0.0029
				(-1.01)
BK/MKT_t				0.0075
				(1.71)
$MOM12_t$				0.0285
				(4.02)
$XTURNOVER_t$				-0.0378
				(-2.49)
No. of Quarters	79	79	79	79
Average R^2	1.18%	0.81%	1.91%	9.47%

Panel B: Raw Returns over 2 Quarters

	1. $\Delta BREADTH_t$ Only	2. $\Delta HOLD_t$ Only	3. $\Delta BREADTH_t$ and $\Delta HOLD_t$	4. Additional Controls
$\Delta BREADTH_t$	3.5015		3.5522	2.0222
	(4.29)		(4.04)	(2.76)
$\Delta HOLD_t$		0.4299	0.1193	0.1291
		(3.54)	(1.22)	(1.45)
$LOGSIZE_t$				-0.0012
				(-0.25)
BK/MKT_t				0.0137
				(1.82)
$MOM12_t$				0.0592
				(4.62)
$XTURNOVER_t$				-0.0705
				(-2.50)
No. of Quarters	79	79	79	79
Average R^2	1.21%	0.73%	1.88%	10.42%

Panel C: Raw Returns over 3 Quarters

	1. $\Delta BREADTH_t$ Only	2. $\Delta HOLD_t$ Only	3. $\Delta BREADTH_t$ and $\Delta HOLD_t$	4. Additional Controls
$\Delta BREADTH_t$	4.4027		4.5356	2.8028
	(4.94)		(4.83)	(3.10)
$\Delta HOLD_t$		0.5917	0.1543	0.1324
		(3.66)	(1.20)	(1.15)
$LOGSIZE_t$				0.0070
				(1.04)
BK/MKT_t				0.0222
				(2.38)
$MOM12_t$				0.0757
				(4.35)
$XTURNOVER_t$				-0.1090
				(-3.09)
No. of Quarters	79	79	79	79
Average R^2	1.15%	0.82%	1.86%	10.09%

Panel D: Raw Returns over 4 Quarters

	1. $\Delta BREADTH_t$ Only	2. $\Delta HOLD_t$ Only	3. $\Delta BREADTH_t$ and $\Delta HOLD_t$	4. Additional Controls
$\Delta BREADTH_t$	4.4693		4.5042	2.9324
	(3.51)		(3.77)	(3.18)
$\Delta HOLD_t$		0.7218	0.2067	0.1448
		(3.25)	(1.13)	(0.95)
$LOGSIZE_t$				0.0132
				(1.64)
BK/MKT_t				0.0293
				(2.60)
$MOM12_t$				0.0836
				(4.16)
$XTURNOVER_t$				-0.1410
				(-3.10)
No. of Quarters	79	79	79	79
Average R^2	1.15%	0.89%	1.92%	9.91%