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Short sales, institutional investors and the cross-section of stock returns

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Abstract

Short-sale constraints are most likely to bind among stocks with low institutional ownership. Because of institutional constraints, most professional investors simply never sell short and hence cannot trade against overpricing of stocks they do not own. Furthermore, stock loan supply tends to be sparse and short selling more expensive when institutional ownership is low. Using institutional ownership as a proxy, I find that short-sale constraints help explain cross-sectional stock return anomalies. Specifically, holding size fixed, the under-performance of stocks with high market-to-book, analyst forecast dispersion, turnover, or volatility is most pronounced among stocks with low institutional ownership. Ownership by passive investors with large stock lending programs partly mitigates this under-performance, indicating some impact of stock loan supply. Prices of stocks with low institutional ownership also underreact to bad cash-flow news and overreact to good cash-flow news, consistent with the idea that short-sale constraints hold negative opinions off the market for these stocks.

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1. Introduction

That stock returns are predictable in the cross-section is well established. A variety of firm characteristics (the book-to-market equity ratio, for example) contain information about a firm's future stock returns (see the survey in Campbell, 2000). What causes this return predictability is less clear. On the one hand, predictability could reflect variation in rational expected returns across firms. On the other hand, it could be the result of mispricing, with overpriced firms earning predictably low future returns and underpriced firms earning predictably high returns. A central element of any mispricing story has to be an explanation as to why these abnormal returns are not arbitraged away. In other words, for mispricing to persist in the presence of sophisticated professional investors, some limits to arbitrage must exist (Shleifer and Vishny, 1997). In this paper, I investigate whether short-sale constraints might play this role. In the presence of short-sale constraints, stocks can become overpriced if some investors are too optimistic (Miller, 1977). If so, return predictability should be most pronounced among short-sale constrained stocks. To the extent that we can identify cross-sectional variation in the tightness of short-sale constraints across stocks, this conjecture constitutes a testable hypothesis.

Short-sale constraints can arise in two ways. First, for institutional and cultural reasons, a general lack of short selling seems to exist in the stock market. I summarize these impediments under indirect short-sale constraints. With indirect short-sale constraints, price efficiency could depend on the actions of the existing shareholders of a stock. Sophisticated investors would sell if a stock gets overpriced. But if the existing owners are not sufficiently sophisticated, the stock could become overpriced, as outside investors cannot sell it without going short. In contrast, if a stock gets underpriced, sophisticated outside investors can always exert buying pressure. Because institutional investors are likely to be more sophisticated than the typical individual investor, indirect short-sale constraints are more likely to affect stocks that are owned mainly by individuals. Second, short selling can be costly. Short sellers must borrow shares from an investor willing to lend. If loan supply is sparse, the short seller may have to pay a significant fee. I refer to this situation as direct short-sale constraints. D'Avolio (2002) shows that the main suppliers of stock loans are institutional investors. Correspondingly, he finds that the degree of institutional ownership explains much of the variation in loan supply across stocks and that stocks with low institutional ownership are more expensive to borrow. Hence, both direct and indirect short-sale constraints are most likely to affect stocks with low institutional ownership.

This makes it feasible to test the short-sale constraints story for cross-sectional return predictability. One immediate implication, and my first hypothesis, is that predictability should be most pronounced among stocks with low institutional ownership. In particular, going down from high to low institutional ownership, sorts on variables that forecast returns should produce an increasing spread in future returns, but mainly so on the short side. Put differently, because short-sale constraints allow only overpricing to persist, but not underpricing, institutional ownership should make a difference when the predictor variable indicates that future returns are low, but not when returns are forecast to be high.

To develop clean tests of this hypothesis, one must address the fact that the degree of institutional ownership is strongly correlated with firm size. Size could proxy for frictions and impediments to arbitrage other than the specific short-sales mechanism that I focus on. Therefore, in portfolio-based tests, I use residual institutional ownership as a sorting variable, which is the percentage of shares held by institutions, adjusted for size in a cross-sectional regression. I also exclude small stocks below the 20th NYSE/Amex size percentile. As cross-sectional predictors, I use the market-to-book ratio, as, for example, in Fama and French (1992); analyst forecast dispersion from Diether, Malloy, and Scherbina (2002); trading volume as in Brennan, Chorida and Subrahmanyam (1998) and Datar, Naik, and Radcliffe (1998), measured as turnover; and firm-level volatility, as in Ang, Hodrick, Xing, and Zhang (2004). Previous studies show that high values of these variables predict low returns and that the effects are distinct from each other.

My findings support the short-sale constraints hypothesis. Holding size fixed, the strength of these return predictability effects increases sharply with lower institutional ownership. For example, within the lowest residual institutional ownership (RI) quintile, high market-to-book (growth) stocks underperform low market-to-book (value) stocks by a stunning 1.47% per month over the sample period 1980-2003. For comparison, in the highest RI quintile, the value premium is only 0.47%. Consistent with the short-sale constraints story, this variation in the value premium across RI quintiles is driven entirely by growth stocks; their average raw returns vary from a dismal -0.01% to 1.06% going from low to high RI. The most striking finding, however, is that the same patterns appear for the other three predictors, too. The under-performance of stocks with high analyst forecast dispersion, high turnover, or high volatility is most pronounced among stocks with low RI, while the returns of stocks with low values of these predictor variables do not vary much with RI. As a result, sorts on these predictors produce a large spread in returns in the low RI quintile (between 0.97% and 1.31% per month), but only a small spread in the high RI quintile (between 0.43% and 0.49%). These results do not seem to be explainable by differential exposure to risk factors. Patterns in abnormal returns relative to the CAPM or the Fama-French three-factor model are similar.

While these results broadly support the short-sale constraints story, they do not reveal whether both direct and indirect short-sale constraints matter. In an effort to disentangle the two channels, I test whether return predictability effects are weaker for stocks held by investors who are large and active lenders of stocks. For these stocks, indirect short-sale constraints could still be binding, but direct short-sale constraints should be relaxed. I find that the under-performance of stocks with high market-to-book, analyst forecast dispersion, volatility, or turnover is mitigated when they are held by the Vanguard 500 (V500) index fund or by Dimensional Fund Advisors (DFA), two of the largest passive investors and major suppliers of stock loans in large- and small-cap stocks, respectively. Stocks held by the V500 fund tend to have higher overall institutional ownership, making the interpretation ambiguous, but DFA stocks do not. This shows that ownership by a large stock lender, and hence the direct short-sale constraints channel, determines to some extent whether cross-sectional return predictability effects can be arbitraged away.

Because institutional and stock lender ownership is a proxy for unobservable short-sale constraints, it is hard to completely rule out alternative explanations. It seems unlikely that institutional ownership is simply proxying for stock-picking skills of institutions (without the short-sales constraints element) because institutional ownership affects predictability only on the short side, and ownership by a passive investor (DFA) also reduces predictability. In addition, the short-sale constraints theory makes specific predictions about the way in which mispricing should arise and persist that are distinct from other explanations. In particular, because short-sale constraints hold negative opinions off the market, prices of stocks with low institutional ownership should underreact to bad news and overreact to good news about future cash flows. I provide empirical support for this conjecture. Sorting stocks on cash-flow news estimated from a vector autoregression (VAR) as in Vuolteenaho (2002) and Cohen, Gompers, and Vuolteenaho (2002), I find that low RI stocks with bad cash-flow news experience a continuation of their bad performance, whereas those with good cash-flow news experience reversals. This striking asymmetry in the reaction to cash-flow news points to a lack of selling pressure from arbitrageurs, in line with the short-sale constraints explanation.

The findings in this paper tie in well with other recent work showing that constraints on short-selling can lead to an optimism-bias in prices (Chen, Hong, and Stein, 2002; Diether, Malloy, and Scherbina, 2002; Jones and Lamont, 2002; Lamont, 2004; Ofek, Richardson, and Whitelaw, 2004; Reed, 2003). I contribute to this literature by providing evidence that short-sale constraints offer an explanation for the persistence of major cross-sectional return anomalies. The paper also connects to other work that examines cross-sectional return predictability conditional on some firm characteristics. Ali, Hwang, and Trombley (2003), for example, show that market-to-book effects are stronger when arbitrage risk is higher and investor sophistication is lower along various dimensions, where institutional ownership is one of their measures. In a contemporaneous paper, Phalippou (2004) also finds that market-to-book predicts returns most strongly among low institutional ownership stocks. My findings show that the Ali, Hwang, and Trombley results hold up when size is controlled for (i.e., they are not driven by the fact documented in Loughran (1997) and Griffin and Lemmon (2002) that the market-to-book effect is stronger among small stocks) and, most important, that the same pattern appears for several other cross-sectional anomalies, too. Moreover, I show that stocks with low institutional ownership misreact to news about future cash flows in a way consistent with the short-sale constraints explanation.

The remainder of the paper is organized as follows. Section 2 discusses the theory of short-sale constraints and develops the hypotheses. Section 3 describes the data and methodology. Section 4 examines how the degree of cross-sectional return predictability varies with institutional ownership. Section 5 examines ownership by large stock lenders. Section 6 investigates the reaction to cash-flow news. Finally, Section 7 concludes.

2. Theory and hypotheses

Short-sale constraints can prevent pessimistic opinions from being expressed in prices. Hence, when investor opinions about the value of an asset differ (i.e., they agree to disagree, for example because they are overconfident) optimistic investors will end up holding overpriced assets, with pessimists sitting on the sidelines (Miller, 1977).[1] In this section, I argue that the degree by which short-sale constraints affect the pricing of stocks should vary with institutional ownership.

2.1. Short-sale constraints and institutional ownership

The following sketch of arguments is based on the premise that financial markets are populated partly by rational investors and partly by some irrational noise traders and that institutional investors tend to belong to the rational group rather than to the noise trader group. In this setting, constraints on institutional trading can lead to mispricing, as they impede the ability of professional investors to trade against noise trader sentiment.

[1] Short-sale constraints also have a number of dynamic implications, which can further amplify mispricing (Harrison and Kreps, 1978; Allen, Morris, and Postlewaite, 1993; Duffie, Gârleanu, and Pedersen, 2002; Scheinkman and Xiong, 2003).

Institutions can be subject to short-sale constraints in two ways. First, institutional investors could generally be unwilling or unable to short for various institutional and cultural reasons. I refer to these constraints as indirect short-sale constraints. For example, Almazan, Brown, Carlson, and Chapman (2004) report that only about 30% of mutual funds are allowed by their charters to sell short and only 3% of funds do sell short. The central implication of indirect short-sale constraints is that the burden of preventing overpricing falls on the existing shareholders of a stock. To be more concrete, suppose that no investor is willing to short. If noise traders are overoptimistic about a firm's prospects, overpricing can be prevented only if some of the existing shareholders sell to accommodate the increased noise trader demand. This requires that a stock's existing shareholders be sufficiently sophisticated. In contrast, if noise traders are too pessimistic, sophisticated new investors can always step in and buy, even if short-sale constrained. Following this logic, a low level of institutional ownership signals in two ways that short-sale constraints are likely to be binding. First, it suggests that sophisticated investors could have sold their shares and are unable to exert further selling pressure without going short.[2] Second, the stock could have characteristics that institutions do not like (see, e.g., Gompers and Metrick 2001), which means that the number of potential sophisticated sellers, in relation to the noise trader population, was low to begin with. Put somewhat differently, in a world with indirect short-sale constraints, arbitrage capacity should be lower for stocks with low institutional ownership, but mostly so on the short side.

Even though only few investors engage in short selling, some do go short. Yet, under certain circumstances, these short sellers can be constrained by the costs of selling short, which I subsume under direct short-sale constraints. To sell short, investors must borrow shares from an investor who owns some of them and who is willing and able to lend. The short-seller must leave collateral with the lender. The lender pays the short-seller interest, the rebate rate, on this collateral. The difference to the interest rate on

[2] This is along the lines of the arguments in Chen, Hong, and Stein (2002) for why the breadth of mutual fund ownership could be a valuation indicator.

cash funds is a direct cost to the short-seller and a benefit to the lender.[3] Obviously, if every investor were willing and able to lend shares in a competitive market, the lending fee would be zero. But, as Duffie (1996) and Krishnamurty (2002) show, if some investors willing to hold overpriced assets do not lend, a strictly positive fee can arise. Unfortunately, existing data sets on stock loans and lending fees, analyzed in D'Avolio (2002), Geczy, Musto, and Reed (2002), and Cohen, Diether, and Malloy (2004) cover time periods of only a few years, which is too short for expected-return tests of the kind conducted in this paper. However, one implication of these models is that short-sale constraints are more likely to be binding for stocks that are predominantly held by nonlending investors. Here again, there is a link to institutional ownership, because, in equity markets, institutional investors provide the bulk of loan supply. Large passive index funds, insurance companies, and pension funds are the most active lenders. Consistent with this fact, D'Avolio (2002) finds that the degree of institutional ownership explains 55% of cross-sectional variation in loan supply and is its most important determinant.[4] Thus, even if some investors are willing to sell short in principle, they could find it costly or impossible to do so in practice when institutional ownership is low, because there is typically little stock loan supply. Hence, both direct and indirect short-sale constraints are most likely to affect stocks with low institutional ownership.

2.2. Hypotheses

Motivated by this theory, I hypothesize that cross-sectional return predictability is caused by mispricing that sophisticated investors cannot eliminate because of short-sale constraints. If so, cross-sectional pricing anomalies should be concentrated among stocks with low institutional ownership.

Hypothesis 1. *Variables that are known to predict returns in the cross-section (e.g., book-to-market, analyst forecast dispersion, turnover, volatility) should be most strongly related to future returns among*

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[3] Further institutional details of the market for stock loans can be found in D'Avolio (2002) and Duffie, Gârleanu, and Pedersen (2002).

stocks with low institutional ownership. This differential in forecasting power should be driven by under-performance of overpriced stocks with low institutional ownership.

Hypothesis 1 follows from the observation that stocks with low institutional ownership are most likely to be subject to indirect and direct short-sale constraints, either because of a lack of sophisticated existing shareholders or because of the loan supply channel. The second part of Hypothesis 1 follows from the fact that short-sale constraints allow only overpricing to persist, but not underpricing. Hence, institutional ownership should not make a difference for stocks that tend to earn high future returns (e.g., value stocks with low market-to-book) and are unlikely candidates for overpricing to begin with.

Given that both direct and indirect short-sale constraints have the same effects with respect to Hypothesis 1, it would also be interesting to investigate whether direct short-sale constraints by themselves have an effect at all. This motivates the second hypothesis.

Hypothesis 2. *Variables that are known to predict returns in the cross-section should forecast returns more strongly among stocks that are not held by large lenders of stocks. This differential in forecasting power should be driven by under-performance of overpriced stocks that are not owned by large lenders of stocks.*

Even for stocks held by only a few institutional investors, loan supply could be adequate to satisfy short-seller demand, provided that at least one of these investors is a sufficiently large and active lender of stocks. Specifically, in the empirical analysis below, I test whether ownership by Dimensional Fund Advisors and the Vanguard 500 index fund has an impact on cross-sectional return predictability. Both investors are known to be large and active lenders of stocks. Given the supply of stock loans they provide, direct short-sale constraints are less likely to bind for the stocks they own.

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[4] More precisely, using data over five quarters from April 2000 to June 2001, he finds that institutional ownership explains between 49% and 62% of cross-sectional variation in loan supply in univariate regressions. Adding other variables such as firm size, book-to-market, and turnover, among others, never adds more than 4% to the R^2.

Finally, the short-sale constraints story also has something to say about how prices should react to news about fundamentals. Whatever the exact nature of unsophisticated investors' reaction to fundamental news, short-sale constraints imply that when the resulting beliefs are too optimistic (that is, in the instance of underreaction to bad news or overreaction to good news) mispricing can arise.

Hypothesis 3. S*tocks with low institutional ownership should underreact to bad cash-flow news and overreact to good cash-flow news.* [5]

Whether the misreaction is more pronounced for good or for bad news depends on whether under- or overreaction is the more prevalent behavioral bias. In any case, the crucial point here is that if there is any misreaction, it should go in the direction predicted by Hypothesis 3, not the opposite. The asymmetric price reaction to good and bad news distinguishes the short-sale constraints theory from other mispricing stories. For example, as an alternative theory, one might conjecture that institutional ownership proxies for the speed of information diffusion, perhaps because it is correlated with analyst coverage, which would imply underreaction to both good and bad news. Tests of Hypothesis 3 should therefore be useful to ascertain that return predictability among stocks with low institutional ownership is driven by short-sale constraints instead of some other impediment to arbitrage. Moreover, the tests can shed some light on how the mispricing causing the predictability arises in the first place.

3. Data and methodology

Data on stock returns are from the Center for Research in Security Prices (CRSP) Monthly Stocks File for NYSE, Amex, and Nasdaq stocks. I eliminate closed-end funds, real estate investment trusts (REIT), American Depository Receipts (ADR), foreign companies, primes, and scores. To correct returns

[5] The underreaction-to-bad news part mirrors the result in Diamond and Verrechia (1987) that short-sale constraints prevent bad private information from being incorporated into prices. However, their model is a common-priors

for delisting bias, I use the adjustment proposed in Shumway (1997) when the delisting return is missing on CRSP. Small-cap stocks below the 20th NYSE/Amex size percentile (i.e., the bottom 20 percent) are excluded from all of the following analysis. Including them would not materially affect the results.

As return predictors, I use market-to-book (M/B), analyst forecast dispersion (ADISP), firm-level volatility (VOL), and turnover (TURN). The book value of equity in the denominator of M/B is taken from the CRSP/Compustat Merged Database, and it is defined as common equity plus balance sheet deferred taxes. At the end of each quarter t, I calculate M/B as market value of equity at the end of quarter t, divided by book value of equity from the most recent fiscal year-end that is preceding quarter-end t by at least six months. Consistent with Fama and French (1993), I exclude firms with negative book values.

Analyst forecast dispersion (ADISP) is measured as in Diether, Malloy, and Scherbina (2002) as the scaled standard deviation of Institutional Brokers Estimates System (I/B/E/S) analysts' current fiscal year earnings per share forecasts. As in their work, I use dispersion calculated from raw I/B/E/S data, because the standard I/B/E/S data have a rounding problem related to stock splits.[6] To make magnitudes comparable across stocks, I follow Johnson (2004) and scale the standard deviation by each firm's total assets. I then average the scaled analyst forecast dispersion figures across months within each quarter. Volatility (VOL) is the standard deviation of a firm's monthly stock returns over the last 12 months. Turnover (TURN) is defined as the number of stocks traded per month as reported on CRSP, divided by the number of shares outstanding, and averaged within each quarter. Because Nasdaq is a dealer market with double counting of dealer buys and sells, the turnover of stocks traded on Nasdaq and NYSE/Amex is not directly comparable (see, e.g., Atkins and Dyl, 1997). As a simple remedy, I divide the turnover of Nasdaq stocks by two. The results are not sensitive to choosing a somewhat different adjustment factor (e.g., 1.7 or 2.3).

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rational expectations model in which there is no mispricing conditional on public information. In contrast, Hypothesis 3 is about misreaction to public information, which can arise when investors have differences in opinion.

[6] I thank Chris Malloy for providing these forecast dispersion data. See Diether, Malloy, and Scherbina (2002) for more details on the splits problem.

Data on institutional holdings are obtained from the Thomson Financial Institutional Holdings (13F) database. I extract quarterly holdings starting in the first quarter of 1980 and ending in the last quarter of 2003. I calculate the share of institutional ownership by summing the stock holdings of all reporting institutions for each stock in each quarter. Stocks that are on CRSP, but without any reported institutional holdings, are assumed to have zero institutional ownership. I correct the data for a problem pointed out by Gompers and Metrick (2001). Spectrum's records of late filings after the 45-day deadline set by the Securities and Exchange Commission (SEC) reflect stock splits that have occurred between the end of the quarter and the filing date. Such late filings account for about 5% of all filings, and they are not directly comparable to those of on-time filers. Because splits are likely to be concentrated in growth stocks, which tend to have good past performance, it is important to correct this shortcoming. I undo this split adjustment using share adjustment factors from CRSP.

3.1. Summary statistics

Table 1 presents some summary statistics on the return predictors M/B (its natural logarithm), ADISP, VOL, and TURN, as well as past 12 month's return (RET12), the fraction of shares outstanding owned by institutions (INST), and log firm size (Log SZ). All statistics are calculated cross-sectionally each quarter and are then averaged across time. Stocks below the 20th NYSE/Amex size percentile are excluded here and in all of the following empirical analysis.

Insert Table 1 near here

Several points are noteworthy. First, the number of observations reported in Panel A for each column shows that data availability requirements lead to different sample sizes for different predictor variables. In particular, M/B requires Compustat data, leading to an average cross-sectional sample size of 2,244 firms. The I/B/E/S data required for ADISP is available for 1,902 firms on average. In the empirical analysis below, I do not impose the requirement that all variables be jointly available, but only those that are used in a particular test. Panel B shows average cross-sectional correlations. The correlations between the candidate return predictor M/B and the variables TURN and VOL are not strong.

Hence, there is reason to believe that to the extent they predict returns, they do so in a somewhat independent fashion. ADISP, TURN, and VOL are more strongly correlated with each other, however, with pairwise correlations ranging from 0.13 to 0.34. Panel B also shows that stocks held by institutions have higher M/B and TURN, lower VOL and ADISP, and they tend to be larger stocks, as reflected in the strong positive correlation between INST and Log SZ (0.53). This is broadly consistent with earlier findings by Gompers and Metrick (2001).

The strong positive correlation between firm size and institutional ownership makes it clear that sorting stocks on raw INST would not provide a conclusive test of the short-sale constraints hypotheses. Sorting on raw INST would largely be similar to sorting on SZ. And it is already well known that many asset-pricing anomalies tend to be stronger for smaller stocks (see, e.g., Griffin and Lemmon, 2002, for the M/B effect). This could have to do with a variety of reasons, including transaction costs and lack of liquidity. The short-sale constraints story makes the more precise prediction that institutional ownership should be the relevant variable. Even holding size fixed, institutional ownership should have an impact on cross-sectional return predictability.

3.2. Residual institutional ownership regressions

In an effort to purge such size effects, the portfolio tests employ residual institutional ownership as a sorting variable, which is obtained as the residual in cross-sectional regressions that include firm size on the right-hand side. The methodology is similar to that used by Hong, Lim, and Stein (2000) in a different context. Some transformations are necessary for these regressions to be well specified. The fraction of institutional ownership (the dependent variable) is bounded by 0 and 1. To map it to the real line, I perform a logit transformation,

$$\text{logit}(\text{INST}) = \log\left(\frac{\text{INST}}{1-\text{INST}}\right), \tag{1}$$

where values of INST below 0.0001 and above 0.9999 are replaced with 0.0001 and 0.9999, respectively. I regress logit(INST) on Log SZ and squared Log SZ. Regressions are run each quarter, and I refer to the residuals as residual institutional ownership (RI). On average, across all quarters, I obtain the following relationship, with autocorrelation-adjusted Fama and MacBeth (1973)-type *t*-statistics in parentheses:

$$\text{logit}(\text{INST}_{i,t}) = \underset{(9.12)}{-23.66} + \underset{(6.52)}{2.89}\ \text{Log SZ}_{i,t} - \underset{(6.19)}{0.09}\ (\text{Log SZ}_{i,t})^2 + e_{i,t}\,. \tag{2}$$

As I show below, this method of sorting on RI obtained from these regressions is effective in creating variation in institutional ownership while keeping size largely fixed.

4. Institutional ownership and the cross-section of stock returns

This section presents tests of Hypothesis 1, which predicts that cross-sectional pricing anomalies should be concentrated among stocks with low institutional ownership. The first set of tests examines each effect individually, using portfolio sorts on residual institutional ownership, intersected with independent sorts on M/B, ADISP, TURN, and VOL. I then proceed with cross-sectional regressions to examine the interplay of these different return predictors.

4.1. Portfolio sorts on residual institutional ownership

In Table 2, stocks are sorted, at the end of each quarter *t*, into five residual institutional ownership classes, using RI as of quarter *t*-2. This time lag for RI helps to ensure that the results are not driven by short-term out-performance of institutional investors' trades of the kind shown, for example, in Chen, Jegadeesh, and Wermers (2000). Portfolios are defined with quintile breakpoints. Before turning to portfolio returns, it is useful to examine the characteristics of stocks across the five RI groups shown in Panel A. These are time-series averages of cross-sectional (equal-weighted) statistics. Consider first the firm size means and medians. Some variation exists in mean market capitalization across portfolios, with the largest firms being in the RI3 category, but this variation is clearly minuscule compared with the variation in size across all stocks on CRSP. In terms of median size, even less variation is evident across portfolios. In contrast, strong variation is seen in institutional ownership from RI1 (mean 0.13) to RI5 (mean 0.53). Hence, sorting on RI apparently does a good job of creating variation in institutional ownership while holding size fixed.

Insert Table 2 near here

In Panels B to E, I intersect these RI_{t-2} sorts with independent sorts on M/B, ADISP, TURN, and VOL, measured at the end of quarter *t*. For all variables, portfolio boundaries are defined by quintile breakpoints. At the end of each quarter, one-fourth of the portfolio is rebalanced, with a holding period of 12 months. Hence, holding periods are overlapping, as in Jegadeesh and Titman (1993), and in any given quarter, the overall strategy holds a portfolio formed at the most recent quarter-end, as well the portfolios formed at the three previous quarter-ends. This methodology allows formation of portfolios at different points during the year, and it increases the power of the tests. Returns in each portfolio are equally weighted and they are reported in percent per month.

Panel B presents the M/B results. The M/B effect is strongly related to RI. The logic behind price-to-fundamentals ratios such as M/B is that overpriced stocks with low future returns should tend to exhibit high ratios. Hypothesis 1 predicts that this under-performance of high M/B stocks should be concentrated among stocks with low RI. As can be seen in the table, this prediction is borne out remarkably well. High M/B stocks under-perform low M/B stocks by 1.47% per month (P1-P5) in the low RI class, but only by 0.47% in the high RI class. The difference in P1-P5 premiums of 1.00% is highly statistically significant, with a *t*-statistic of 3.80. This shows that the impact of institutional ownership on the M/B effect shown in Ali, Hwang, and Trombley (2003) holds up after controlling for size and over a sample period more than twice as long as theirs.

Moreover, the difference in P1-P5 premiums across RI quintiles comes almost entirely from variation in the returns of high M/B stocks (P5). Over the course of the sample period 1980-2003, high M/B stocks in the low RI group earned a negative raw return of only -0.01% per month. By contrast, those with high RI earned 1.06%. The difference of 1.07% is highly significant (*t*-statistic 4.91). In contrast, returns of low M/B stocks do not vary much with RI. This asymmetric impact of institutional ownership on low versus high M/B stocks is exactly what the short-sale constraints theory implies, as stated in Hypothesis 1. Indirect and direct short-sale constraints prevent sophisticated investors from trading effectively against overpricing of high M/B (growth) stocks when institutional ownership is low. By contrast, low M/B (value) stocks are, if anything, under- instead of overvalued to begin with. Hence, there is no reason to expect short-sale constraints to have an impact. Even if short-sale constraints bind, new investors can always step in and buy an undervalued stock. This asymmetry also shows that RI is unlikely to proxy simply for skilled trading by institutional investors because under this alternative hypothesis, without the short-sale constraints element, RI would have to be positively related to returns irrespective of the level of M/B.

These results appear to be at odds with the notion that value (low M/B) stocks earn higher returns than growth (high M/B) stocks because they are riskier, as proposed by Fama and French (1993). Under this risk hypothesis, there is no obvious reason why the magnitude of the premium should vary with institutional ownership. Nevertheless, to check whether covariance with risk factors might explain some of the results, I have run single factor (CAPM) and multi-factor (Fama-French three-factor model) time-series regressions. In the table, I report intercepts of these time-series regressions, along with zero intercept test *t*-statistics in parentheses, for the P1-P5 (low minus high M/B) zero investment portfolios.

As can be seen in Panel B, adjusting for exposure to these factors changes little. While the magnitude of the P1-P5 premiums goes up a bit under the CAPM, the difference RI5-RI1 is almost unchanged (1.08%, *t*-statistic 2.96).[7] Similarly, the Fama-French three-factor intercepts are somewhat lower than the raw returns, but for low RI stocks there still remains an unexplained P1-P5 premium of 1.09% per month (*t*-statistic 4.13), and a difference RI5-RI1 of 1.16% (*t*-statistic 3.58). Untabulated Gibbons, Ross, and Shanken (1989) multivariate tests also easily reject the hypothesis that intercepts of the 25 portfolios are jointly equal to zero. Overall, these test results suggest that at least a substantial part of the value premium originates from overpricing of high M/B stocks and is not compensation for factor risk. This in turn calls into question that the premium earned by the value-growth return spread HML in the Fama-French model is compensation for factor risk to begin with. Using the three-factor model as a risk model could in fact eliminate some abnormal returns caused by misprcing. In any case, the results in Panel B do not seem to be driven by some intricate correlation between residual institutional ownership and risk exposure.

Strikingly similar patterns can also be observed for other return predictors. Panel C presents the results of sorts on ADISP, i.e., the Diether, Malloy, and Scherbina (2002) analyst forecast dispersion measure. In their paper, they propose that ADISP predicts returns because it proxies for differences in opinion, which lead to an optimism-bias in prices when short-selling is constrained. As Panel C shows, the patterns in returns across RI groups fit nicely with this interpretation. The highest difference in returns between low and high ADISP stocks (P1-P5) arises in the RI1 category, that is, among stocks with low residual institutional ownership (0.97%, *t*-statistic 1.87). Going to the RI5 group, the P1-P5 premium is reduced to 0.49% (*t*-statistic 1.55). As predicted by Hypothesis 1, RI makes a large difference (RI5-RI1) for high ADISP stocks (0.54%, *t*-statistic 2.47), which can be overpriced according to the differences-in-opinion story, while low ADISP stocks have relatively high returns irrespective of RI with a return differential RI5-RI1 of only 0.07% (*t*-statistic 0.36). Although the variation in ADISP predictability with RI is of economically important magnitude, the significance levels for some of the zero-investment portfolios are not as high as in the M/B case. Adjusting for factor risk again makes little difference to the results, as is evident from the CAPM and three-factor intercepts. Overall, the results on ADISP, while less statistically reliable, conform closely to the patterns observed in Panel B for M/B. This is striking, because ADISP and M/B are almost uncorrelated (-0.01, see Table 1) and thus seem to capture two distinct effects.

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[7] Furthermore, allowing for time-variation in betas and the market risk premium would be unlikely to change these results by any economically significant magnitude given the arguments and evidence in Lewellen and Nagel (2005).

In Panel D, I intersect the RI sorts with sorts on TURN, that is, each stock's turnover over the last quarter, based on earlier evidence by Datar, Naik, and Radcliffe (1998) and Brennan, Chorida, and Subrahmanyam (1998) that stocks with high trading volume tend to earn low future returns. Here, too, the patterns in average returns bear striking resemblance to Panel B. Stocks with high TURN and low RI earn a paltry 0.16% per month, leading to a premium for low turnover stocks in the low RI group of 1.12% (*t*-statistic 2.16). Among high RI stocks, in contrast, the P1-P5 premium is much lower (0.43%, *t*-statistic 1.67). As in Panels B and C, the bulk of the effect comes from the overpriced side (high TURN, i.e., P5), where the difference in returns between high and low RI stocks amounts to 0.92% (*t*-statistic 2.71), compared with 0.22% (*t*-statistic 2.02) for low TURN stocks, which is again in line with Hypothesis 1. Adjusting for factor risk does not change the magnitude of the effects by much, with the only noteworthy change being the fact that the difference between the RI5 and RI1 P1-P5 portfolios is no longer significant at the 5% level (*t*-statistic 1.30) using the three-factor model. One has to bear in mind, though, that the results in Panel B cast doubt on the validity of the three-factor model as the proper benchmark.

Finally, Panel E reports returns for sorts on 12-month stock return volatility (VOL). Once more the predictions of Hypothesis 1 are borne out remarkably well. Stocks with high VOL (P5) have low future returns, consistent with Ang, Hodrick, Xing, and Zhang (2004), but particularly so if institutional ownership is low (RI1), with an average return of only 0.08% per month over the 1980-2003 sample period. The P1-P5 premium is 1.31% (*t*-statistic 2.31) in the low RI group, compared with 0.45% (*t*-statistic 1.22) in the high RI group. Again, this difference originates mainly from potentially overpriced high VOL stocks for which institutional ownership makes a large difference, while institutional ownership has little effect on returns of low VOL stocks. Adjusting for factor risk basically leaves the results unchanged, both in terms of magnitude and statistical significance.

4.2. Cross-sectional regressions

To explore the interrelationships of these different return predictability effects, Table 3 presents a series of cross-sectional regressions. The point of this paper is not to show that these effects are distinct, but it is nevertheless interesting to see whether the interaction effects with institutional ownership hold up when the predictors are examined jointly. Moreover, the regression tests also provide a useful check on the methodology used in Table 2. Instead of using residual institutional ownership as an explanatory variable, the regressions employ unadjusted institutional ownership with separate size controls.

Cross-sectional regressions are run every quarter *t*, from 1980 to 2003. As before, stocks below the 20th NYSE/Amex size percentile are excluded. Dependent variable is the return over the four quarters from *t*+1 to *t*+4, which is regressed on quarter *t* stock characteristics, including interactions with SZ and INST. Because the predictor variables do not have well-behaved cross-sectional distributions (TURN and VOL, for example, frequently have large outliers), I transform all return predictors into decile ranks each quarter. The decile ranks are then scaled such that their values fall into the interval from 0 to 1. This transformation also facilitates the interpretation of coefficient estimates, and it is done before forming the interaction terms. The coefficient estimates shown in the table are the time-series averages of these quarterly estimates. Standard errors are computed in the usual Fama-MacBeth fashion from the time-series standard deviation of coefficient estimates, adjusted for autocorrelation using the Newey and West (1987) method.

Insert Table 3 near here

In the first column of Table 3 (Model 1), future returns are regressed on all four predictors M/B, ADISP, TURN, and VOL. The coefficient estimates are broadly consistent with the earlier portfolio results. All coefficients estimates are negative, ranging from –3.10 for VOL to –4.98 for ADISP. Although only the coefficient on TURN is significantly different from zero at the 5% level (*t*-statistic 2.84), the similarity in magnitudes shows that none of the predictor variables completely subsumes the effects of the other. To get a sense of the magnitudes, note that a coefficient of –4.98 for ADISP implies a differential in average returns going from the lowest to the highest ADISP decile rank of 4.98% per year, holding M/B, TURN, and VOL fixed.

Models 2 to 5 look at each effect in isolation and at its interaction with institutional ownership (INST) and firm size (SZ). The coefficient on M/B in Model 2 implies that, among the smallest stocks with lowest institutional ownership (for which the transformed INST and SZ variables take values of zero), the difference in returns between top and bottom M/B deciles is 18.74% per year (*t*-statistic 3.87). The interaction terms show that holding INST fixed and going to the highest SZ decile has little effect; it reduces the low M/B premium by only 1.77%. In contrast, if we hold SZ fixed and go to the highest INST decile (with the transformed INST variable going from 0 to 1), the M/B effect basically disappears, as the coefficient on the interaction term with INST is 15.48 (*t*-statistic 3.98), leaving a low M/B premium of only 18.74 - 15.48 = 3.26% per year. However, one should not take this exercise too literally, as only few stocks in the smallest size group have high institutional ownership. Nevertheless, the results confirm the basic message from the portfolio sorts: The strength of the M/B effect varies strongly with institutional ownership, even if firm size is held fixed, consistent with the short-sale constraints theory.

Model 3 shows that similar patterns appear for ADISP, albeit of lower magnitude and lower levels of significance. Among small stocks with low institutional ownership, the low ADISP premium amounts to 10.67% per year (*t*-statistic 1.74). Increasing SZ while holding INST fixed basically leaves the magnitude of the low ADISP premium unchanged, as is evident from the small value of the coefficient estimate (-1.24, *t*-statistic 0.25). Going from low to high INST while holding SZ fixed instead reduces the ADISP premium by 4.80%. As a caveat, though, the *t*-statistic is only 1.25 and hence the point estimate is somewhat unreliable.

Models 4 and 5 also exhibit the familiar pattern. There is a high premium for low TURN stocks among stocks with low INST and small SZ (coefficient estimate –11.42, *t*-statistic 2.12). Increasing SZ has relatively little effect, reducing the low TURN premium by 2.32% (*t*-statistic 0.46), while increasing INST has a bigger effect of 5.90% (*t*-statistic 1.25). But again, the point estimate on the interaction term here is unreliable. Small cap stocks with low institutional ownership exhibit a large low VOL premium of 13.35% (*t*-statistic 1.96). Variation in SZ independent of INST has little effect (coefficient estimate –2.14, *t*-statistic 0.43), while going to high INST, holding SZ fixed, basically eliminates the low VOL premium (coefficient estimate 13.06, *t*-statistic 2.60).

Model 7 looks at the joint effect of all predictor variables and their interaction terms. Unfortunately, with a large number of explanatory variables and interaction terms, obtaining results that are statistically reliable is difficult. As a partial remedy, I drop the interaction terms with SZ (the results on Models 2 to 6 show that variation in SZ has relatively little effect on the strength of the predictive relationship between M/B, ADISP, VOL, TURN, and future returns). The coefficient estimates on M/B, ADISP, TURN, and VOL in Model 7 are negative, as before. However, the magnitudes are clearly reduced compared with the individual effect regressions in Models 2 to 6. This is not surprising. After all, if the effects were fully independent and additive, this would imply that a strategy of shorting stocks with low INST and SZ and simultaneously high M/B, ADISP, TURN, and VOL would produce implausibly high returns. Compared with Model 1, however, the coefficient estimates are larger in magnitude except for VOL, showing that the effects tend to be concentrated among stocks with low INST. The estimates for the interaction terms show that increasing INST tends to reduce the predictive power of M/B, ADISP, and TURN, again with the exception of VOL. The standard errors are large, though, and so there is not much one can say with statistical reliability. Part of the reason that it is difficult to obtain statistical precision in this regression is that ADISP, VOL, and TURN have a fairly strong positive correlation. Model 8 therefore drops the ADISP variable, which leads to somewhat larger point estimates and higher *t*-statistics, in particular for the M/B variable and its interaction with INST. Also, the sign of the coefficient estimates on VOL are now in line with the earlier findings in Model 5.

The picture that emerges from Table 3 basically confirms that institutional ownership affects the predictive power of M/B, ADISP, TURN, and VOL in the way predicted by Hypothesis 1. Although it is clearly difficult to disentangle the marginal explanatory power of these four predictor variables with statistical precision, the effects do seem to be distinct, albeit not completely unrelated.

4.3. Further variations

Before proceeding with tests of the other hypotheses, I briefly report some further untabulated results on variations of my basic tests of Hypothesis 1 and some robustness checks.

4.3.1. Subperiods

The concentration of return predictability among stocks with low residual ownership shows up in different subperiods. For example, cutting the sample period in half and repeating the portfolio sorts of Table 2 (Panel B) for the period September 1981 to June 1992 yields a low M/B premium of 1.39% per month in the low RI group versus 0.49% in the high RI group. From September 1992 to December 2003 the magnitudes are similar, with 1.54% and 0.45%, respectively. For the other return predictors, the results largely mirror those for M/B, with the exception of ADISP, for which RI makes no difference in the first subperiod (P1-P5 returns are 0.87% for low RI and 0.89% for high RI).

As a caveat, during the burst of the technology bubble from March 2000 to the end of 2003, the performance of high M/B stocks relative to low M/B stocks, for example, was dismal irrespective of their level of institutional ownership (-1.60% for low RI versus –1.72% for high RI). To some extent, this is not too surprising. Brunnermeier and Nagel (2004) show that sophisticated investors (hedge funds) were riding the bubble, holding long positions in stocks with extreme valuation levels during the time before March 2000, and they argue that short-sale constraints were not the crucial limit to arbitrage during this period (see, also, Lamont and Stein, 2004). Seen from this perspective, short-sale constraints are unlikely to explain the entire low M/B premium. During some periods, high M/B stocks might be overvalued and arbitrageurs unwilling to short them for other reasons than those that are the focus of this paper.

4.3.2. Alternative return predictors

The number of return predictors that appear in the literature is simply too large to check whether they all relate in the same way to institutional ownership. For this reason, I focus on variables that have recently received attention, but the results hold for several other predictors, too. Results for sorts on price-to-sales, price-to-earnings, and price-to-cash flow largely mirror those for market-to-book in Table 2. The untabulated robustness checks also include tests using the Chen, Hong, and Stein (2002) breadth of mutual fund ownership variable. However, in the years after the end of their sample period in 1998, stocks with decreases in breadth of ownership outperformed those with increases in breadth by a large margin (the reverse of the effect reported in their paper and perhaps related to the technology bubble) to the extent that the effect is almost eliminated over the full sample period 1980 to 2003. Hence, there is little left to explain. Before 1999, though, the breadth of ownership effect, too, is most pronounced among stocks with low RI and virtually absent when RI is high, similar to the results for the other return predictors.

4.3.3. Disaggregation by size

While using residual institutional ownership as a sorting variable ensures that the tests do not simply pick up size-related variation in predictability, the impact of institutional ownership could nevertheless be concentrated among relatively small stocks. There is reason to believe that this is the case, because most stocks with low institutional ownership are small-cap stocks. For example, doing an independent 3x3x3 sort on M/B, SZ, and INST is basically impossible as in some years fewer than 5 stocks are in some of the extreme portfolios. Sorting instead on INST within the SZ groups, I find that the impact of INST on the return premium of low M/B, ADISP, TURN, or VOL stocks is roughly similar in magnitude for small- and mid-cap stocks. In both size categories, the premium shrinks by 0.40% to 0.90% going from low to high INST. Within the large SZ group the effect of INST is small for M/B (about 0.20%) and close to zero for the other variables. However, for large SZ stocks there is less of a return premium to be explained in the first place. Hence, the effects shown in Table 2 derive mainly from the small- and mid-cap stocks within each portfolio. From the short-sale constraints perspective, this makes sense. Given that most of the stocks in the large-cap group are held by actively lending index funds, loan supply should rarely be scarce for these stocks. Moreover, low INST stocks in the large SZ group have much higher average INST (about 0.30) than the low INST stocks in the small SZ group (about 0.15). Hence, only few large stocks have truly low institutional ownership.

4.3.4. Increasing the lag for residual institutional ownership

Using longer lags for institutional ownership changes little. With RI lagged by six quarters (instead of two) the low M/B premium still varies from 1.23% to 0.37% going from low to high RI stocks; the difference of 0.86% is almost as large as the one shown in Table 2 and is highly significant (*t*-statistic 3.59). For the other three predictors, the magnitude by which P1-P5 premiums vary with RI is virtually identical to the results shown in Table 2. All vary from RI1 to RI5 by amounts that are significantly greater than zero at a 5% level in one-sided tests. This underscores further the view that RI does not simply proxy for some short-term information contained in institutional trades.

5. Ownership by large stock lenders

In an effort to distinguish the effects of direct and indirect short-sale constraints, this section turns to tests of Hypothesis 2. More precisely, the objective is to check whether direct short-sale constraints, driven by scarce supply of lendable shares, matter at all. To check this, I examine holdings of two of the largest stock lenders in large- and small-cap stocks, respectively. For stocks held by large stock lenders, loan supply should be abundant in most instances. First, from the quarterly Thomson Mutual Fund Files, I extract quarterly holdings of the Vanguard 500 index fund, which tracks the Standard & Poor's 500 index. Second, I extract holdings of Dimensional Fund Advisors from the Thomson 13F files. DFA is the largest investor in U.S. small-cap stocks.[8] DFA follows a passive investment strategy, albeit not by strictly tracking an index. Portfolio weights on individual stocks are allowed deviate from weights in the benchmark, depending on trading cost considerations (see Keim, 1999). Most important for the purposes

[8] At the end of 2002, DFA managed assets worth $33 billion. The V500 fund had $68 billion under management.

of this paper is that DFA is a major lender of stocks. Geczy, Musto, and Reed (2002) report that DFA had outstanding stock loans on 499 stocks on December 31, 1998. Hence, even for small caps it should usually be easy for brokers to locate a loan when a stock is held by DFA, and short selling should thus be relatively unconstrained.

In Table 4, stocks are sorted into three groups depending on ownership, lagged by two quarters as before. The sample period starts in July 1983, two quarters after the first 13F filing of DFA appears in the Thomson database. The first column (others) presents returns for stocks held neither by DFA nor by the V500 fund. Stocks held by DFA, but not by the V500 fund, are in the second column, and stocks held by the V500 fund are in the third. Panel A reports some characteristics of stocks in these three groups. Naturally, stocks held by the V500 fund are larger and have higher institutional ownership than stocks in the others column and stocks held by DFA. Hence, the comparison of others with V500 is somewhat ambiguous, as any differences in predictability of returns could also be driven by the higher average institutional ownership of V500 stocks via the indirect short-sale constraints channel. However, differential predictability effects between others and DFA cannot easily be attributed to the indirect channel, because, as the table shows, both groups of stocks are similar in terms of typical size and institutional ownership. What distinguishes them is that, for stocks held by DFA, we know that at least one of their large shareholders is willing to lend shares. In contrast, stocks in the others group are less likely to have an active lender among their shareholders and are therefore more likely to be affected by direct short-sale constraints.

Insert Table 4 near here

Panel B presents portfolio sorts on M/B. As predicted by Hypothesis 2, high M/B stocks under-perform most strongly when they are not held by DFA and the V500 fund. As a consequence, the low M/B premium is 1.07% per month (*t*-statistic 3.04) for others stocks, compared with 0.69% (*t*-statistic 1.88) for DFA stocks. The differential of 0.38% (*t*-statistic 2.34) is significantly greater than zero at conventional significance levels. The low M/B premium is further reduced among V500 stocks (0.47%, *t*-statistic 1.64), but this effect is more ambiguous, given that V500 stocks typically also have higher institutional ownership. The CAPM and three-factor intercepts show that adjusting for exposure to risk factors has little impact on the results. Interestingly, returns on low M/B stocks do not vary much across the three ownership groups. Consistent with Hypothesis 2, the differential in premiums across ownership groups is largely driven by high M/B stocks. The results suggest that loan supply availability does matter for how much M/B stocks can become overpriced. Indirect short-sale constraints alone cannot explain the differential in premiums between others and DFA stocks.

Alternatively, one might suspect that some other difference in firm characteristics between others and DFA stocks could play a role in generating these results. DFA is a passive manager, but it employs some fixed portfolio eligibility rules. As detailed in Keim (1999), DFA does not invest in stocks during the first year after their initial public offering (IPO), in Nasdaq stocks with fewer than four market makers, and in low priced stocks (below $2). To check the effect of these rules, I have repeated the exercise in Panel B (and in the panels below) using only stocks priced above $2 and with a CRSP price history of at least one year. The results are similar. The market maker requirement should not be material, because all stocks below the 20th NYSE/Amex size percentile are already excluded in Table 4, which deletes almost half of all Nasdaq stocks. Overall, it seems unlikely that the results are driven simply by portfolio eligibility rules.

Panel C looks at the intersection with sorts on ADISP. Here, too, a substantial reduction is evident in the under-performance of high ADISP stocks going from others to DFA stocks. The high ADISP premium declines from 0.97% (*t*-statistic 1.92) to 0.56% (*t*-statistic 1.26). The difference is 0.41% with a *t*-statistic of 2.07. The P1-P5 differential among V500 stocks is similar in magnitude to that among DFA stocks. The results in Panel D for TURN look a bit different. While the direction of the effect is still consistent with Hypothesis 2 (the low TURN premium is smaller among DFA stocks than among others) the magnitude of the difference is small (0.18%, *t*-statistic 1.37). The big decline happens here going to the V500 category, in which there is basically no premium for low TURN stocks at all (P1-P5 earns –0.02%, *t*-statistic 0.06). Finally, Panel E examines sorts on VOL, which strongly exhibit the familiar pattern. High VOL stocks in the others category under-perform low VOL stocks by 1.39% per month (*t*-statistic 2.36), while the corresponding return differential within the DFA group amounts to only 0.57% (*t*-statistic 1.11). The difference between the two of 0.82% is significantly greater than zero at conventional significance levels. There is no low VOL premium among V500 stocks (0.09%, *t*-statistic 0.16). Again, adjusting for factor risk essentially makes no difference to the results.

In short, these results suggest that direct short-sale constraints play a role in impeding arbitrage activity, at least among small-cap stocks. The differentials in stock return predictability between DFA stocks and stocks held neither by the V500 fund nor by DFA cannot be explained by the indirect channel.

6. Asymmetric reaction to cash-flow news

As a final test of the short-sale constraints story, I investigate Hypothesis 3, which predicts that stock prices of firms with low institutional ownership should react asymmetrically to news about future cash flows (they should underreact to bad cash-flow news and overreact to good cash-flow news) because short-sale constraints hold negative opinions off the market. One might be tempted to investigate this hypothesis by looking for variation in return momentum and reversals across stocks. Yet, past returns could be imperfect proxies for cash-flow news. For example, if a stock becomes more overpriced, returns can be high in the absence of news about fundamentals. For this reason, I follow Vuolteenaho (2002) and decompose firm-level stock returns into news about future cash flows and news about expected returns (mispricing) using a vector autoregression approach. I use the VAR methodology to extract cash-flow news from stock returns and I then sort stocks into portfolios based on these cash-flow news. Vuolteenaho (2002) and Cohen, Gompers, and Vuolteenaho (CGV, 2002) show that stock prices typically underreact to cash-flow news, particularly so for small-cap stocks with bad news. Hypothesis 3 suggests a new twist on this, as underreaction to bad news should be most pronounced among low institutional ownership stocks (even holding size fixed), and these stocks should also overreact to good news.

6.1. VAR methodology

Vuolteenaho (2002) follows Campbell (1991) and decomposes unexpected stock returns into news about future cash flows and news about future expected returns, respectively, plus an approximation error,

$$r_t - E_{t-1} r_t = \underbrace{\kappa_t + \Delta E_t \sum_{j=0}^{\infty} \rho^j e_{t+j}}_{N_{cf}} - \underbrace{\Delta E_t \sum_{j=1}^{\infty} \rho^j r_{t+j}}_{N_r} , \qquad (3)$$

where ΔE_t denotes the change in expectations from t-1 to t, e_t is the log clean-surplus accounting return on equity (ROE), r_t is the firm-level log stock return, κ_t is the approximation error, and ρ is a constant that I set to 0.98 (after estimating it as in Vuolteenaho, 2002). A VAR provides forecasts of future r_t at each time, which permits calculation of expected return news $N_{r,t}$ as in Eq. (3). Cash-flow news can then be defined as the residual via $N_{cf,t} = r_t - E_{t-1}r_t + N_{r,t}$, i.e., it includes the approximation error κ_t. The VAR assumes a linear evolution of each firm's state vector $z_{i,t}$,

$$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t} , \qquad (4)$$

where the transition matrix Γ is assumed to be constant across firms and time. The first element of $z_{i,t}$ contains the log stock return and expected return news can then be calculated as $N_{r,t} = e1'\rho\Gamma(I-\rho\Gamma)^{-1}u_{i,t}$. Cash-flow news can be backed out indirectly as $N_{cf,t} = (e1' + e1'\rho\Gamma(I-\rho\Gamma)^{-1})u_{i,t}$, where $e1 = [1 \;\; 0 \;\; \ldots \;\; 0]'$. Intuitively, the indirect method works as follows. When a stock's price goes up by \$1, but contemporaneous changes in the VAR state variables indicate that expected returns have gone up, too (e.g., the book-to-market ratio increased), then this method attributes more than \$1 to cash-flow news and the difference to expected return news. Put differently, in this example, the VAR detects that prices have underreacted to cash-flow news. The implicit assumption underlying this interpretation is that the variables in the state vector do not pick up cross-sectional variation in rational discount rates, and thus, expected return news can be interpreted as changes in mispricing. Alternatively, the VAR can be used to forecast and discount the cash flows in Eq. (3) directly. With roe^{CS} as the second element of the state vector, cash-flow news can then be calculated as $N_{cf,t} = (e2' (I-\rho\Gamma)^{-1})u_{i,t}$, where $e2 = [0 \;\; 1 \;\; 0 \;\ldots\; 0]'$.

Vuolteenaho (2002) discusses in more detail the assumptions that go into this VAR-based return decomposition.

As a caveat, if the reaction of stock prices to cash-flow news is asymmetric, as Hypothesis 3 suggests, a linear VAR is misspecified. To account for this asymmetry, the state variables would have to follow a more complicated nonlinear law. However, I use cash-flow news only as an input for binning into coarsely defined portfolios. As long as the VAR gets cash-flow news roughly right, a linear VAR should be sufficient for this purpose. If the VAR were used instead to estimate long-run impulse-response functions, for example, results might be more sensitive to nonlinearity.

As in Vuolteenaho (2002), the VAR state vector includes the log stock return over 12 months (*ret12*); the log clean-surplus accounting return on equity (roe^{CS}), where clean-surplus earnings are calculated as the change in book equity adjusted for dividends and equity offerings; the log GAAP accounting return on equity (roe^{GAAP}), calculated as earnings before extraordinary items divided by last period book value of equity; and the log book-to-market ratio (*b-m*).[9] To be able to rebalance cash-flow news portfolios at quarterly frequency, as in Table 2, I use quarterly accounting data from Compustat implement the VAR. Stock returns and return on equity are calculated over the same (overlapping) 12-month periods. All variables are transformed and market-adjusted, i.e., demeaned by their cross-sectional averages each year, as in Vuolteenaho (2002).

I estimate the VAR by running quarterly cross-sectional regressions, averaging coefficients over time, and using the time-variation of coefficient estimates to calculate cross-correlation consistent Fama-MacBeth-type standard errors, adjusted for autocorrelation. Panel A of Table 5 presents the estimates. The results are consistent with the stylized facts on the cross-section of stock returns and similar findings obtained by CGV using annual data. In short, high *ret12*, roe^{GAAP}, and *b-m* predict high future returns, and

[9] It is difficult to provide a simple one-size-fits-all adjustment of clean-surplus earnings for equity issues that treats all different form of equity issues (e.g., seasoned offerings and stock-financed takeovers) appropriately. As an approximation, I use Vuolteenaho's method, which assumes that equity issues at book-to-market above or below one lead to a partial revaluation of existing shareholder's book equity toward market value. From the perspective of an existing shareholder, this can be thought of as a partial sale of their stake at the time of the event.

roe^{GAAP} and *b-m* are strongly persistent. In unreported tests, I also experiment with a VAR specification that allows the transition matrix to differ by residual institutional ownership quintile, assuming that group assignments are permanent. This allows for different degrees of return predictability across RI quintiles along the lines of Section 4. However, it turns out that for the purpose here (that is, portfolio sorts based on cash-flow news) allowing the transition matrix to be different across RI quintiles does not have an economically significant impact on any of the results. For simplicity, I therefore report the results obtained using a common transition matrix.

Insert Table 5 near here

6.2. Returns to portfolios sorted on cash-flow news

In Panel B of Table 5, stocks are sorted into quintile portfolios by their cash-flow news over the 12 months prior to portfolio formation. Cash-flow news is calculated indirectly, i.e., as the sum of unexpected return and expected return news, where the latter is obtained from VAR forecasts. Panel C considers sorts on directly calculated cash flow news. In both panels, cash-flow news sorts are intersected with independent sorts on RI, just as in Table 2. Hypothesis 3 predicts that low RI stocks with bad cash-flow news should experience low future returns, as short-sale constraints prevent a timely incorporation of bad news into prices. Moreover, low RI stocks with good cash-flow news should have low future returns, as some investors might overreact to the good news, which can result in overpricing and subsequent reversals when short-selling is constrained. The return figures shown in Panel B confirm these predictions. Low RI stocks in the lowest cash-flow news category (P1) have dismally low returns of 0.23% per month. For comparison, stocks with little cash-flow news (P3) have a mean return of 1.16%. The difference of 0.93%, i.e., the return on a cash-flow loser momentum strategy that is short P1 and long P3, is significantly different from zero at conventional significance levels (*t*-statistic 2.30). This finding is consistent with the view that stocks with low RI underreact to bad news. For stocks with high RI, in contrast, the under-performance of cash-flow news loser stocks is much less pronounced.

There is also some support, albeit not as strong, for overreaction to good news. Low RI stocks with good cash-flow news (P5) earn 0.70%, which is 0.46% lower than those in P3, but the difference is not reliably different from zero (*t*-statistic 1.62). Clearly, the middle portfolio P3 is perhaps not the best benchmark with which to compare cash-flow winners and losers. After all, stocks with extreme realizations of cash-flow news could differ in many respects from stocks with relatively little cash-flow news. An alternative is to compare returns within the same cash-flow news group, but across RI quintiles. The estimates for differences in mean returns between RI1 and RI5 are a bit more precise, probably because stocks in the same cash-flow news category have a higher degree of comovement. In any case, low RI cash-flow news losers (P1) under-perform high RI cash-flow news losers by 0.53% per month (*t*-statistic 2.29), again suggesting underreaction of low RI stocks to bad news. Using this way of comparison, the evidence of overreaction to good news is statistically stronger. Low RI cash-flow news winners under-perform their high RI counterparts by 0.56% (*t*-statistic 3.32). Looking only at winner minus loser returns (P5-P1), as in a standard momentum strategy, obscures this heterogeneity across RI quintiles. Returns to this strategy do not vary much with RI because the poor performance of low RI winners partly offsets the gains from shorting low RI losers.

Using directly calculated cash-flow news delivers somewhat stronger results. As shown in Panel C, low RI losers now earn only 0.03%, about 1.18% less than low RI stocks with little cash flow news (P3), with a *t*-statistic for the difference of 2.93. Looking across columns, low RI losers also under-perform loser stocks in the high RI category by 0.70% (*t*-statistic 3.06). Hence, again, evidence exists for underreaction to bad news among low RI stocks. Low RI winners also perform poorly, under-performing low RI stocks with little cash-flow news by 0.58% (*t*-statistic 2.08) and winners with high RI by 0.65% (*t*-statistic 3.72). This means that the results are robust to the way in which cash-flow news is calculated. Portfolios sorted on directly calculated cash-flow news based on forecasts of future clean-surplus return on equity deliver result similar to the indirect method in Panel B. Moreover, untabulated tests show that portfolios sorted on simple 12-month stock returns (i.e., momentum) exhibit patterns in returns that are quantitatively similar to those of Panels B and C.[10] However, for simple return momentum sorts the interpretation as misreaction to fundamental news is less clear.

6.3. Long-horizon returns

Two concerns remain with the results presented in Table 5. First, the cash-flow news strategies in Panels B and C are not implementable investment strategies, because they would require investing right at the fiscal quarter-end, when the accounting data needed to compute cash-flow news are not fully available (although stock returns and accounting data from earlier quarters might provide most of the required information). While the timeliness of the reaction to news is the main focus here, not implementability, it would still useful to check whether the results are driven by the first few months after portfolio formation. Second, the interpretation of poor performance of low RI losers and winners as underreaction to bad news and overreaction to good news, respectively, relies on there being no reversals of this performance in the long run.

Fig. 1 addresses both concerns by showing long-run cumulative returns of the cash-flow news winner and loser strategies (P5-P3 and P3-P1) in the low RI category from one to 36 months after portfolio formation. Dashed lines show +/- 2 standard error bands. The top graph shows the loser strategy. The poor performance of low RI losers has a largely permanent effect on prices, consistent with the underreaction-to-bad-news story. Cumulative returns drift upward until about month 18. Subsequently, there is only a very weak reversal.[11] Naturally, as horizons get longer, standard error bands also widen, making inference less reliable. Overall, only little of the cumulative returns comes from the first three months following portfolio formation, which suggests that implementability is not an issue.

Insert Fig. 1 near here

The second graph presents cumulative returns for the low RI cash-flow news winner strategy (P5-P3). As it shows, the poor returns of high cash-flow news stocks continue beyond the 12-month

[10] The results are available from the author on request.

[11] The periodic fluctuations apparent in the graph seem to be a typical phenomenon in cumulative long-horizon returns on momentum strategies (see, e.g., Jegadeesh and Titman, 2001; Heston and Sadka, 2004).

horizon considered in Table 5. There is no reversal of the initial under-performance. Also, under-performance does not set in until about six months after portfolio formation. This finding fits well with the overreaction-to-good-news story. Good news leads to overpricing, which tends to persist and only slowly reverts because short-sale constraints impede arbitrage, resulting in low long-run returns.

7. Summary and conclusions

The evidence presented in this paper suggests that short-sale constraints play an important role in the cross-section of stock returns. I argue that short-sale constraints, both indirect institutional constraints and direct short-selling costs, should mainly affect stocks with low institutional ownership. Consistent with these arguments, I find that the forecasting power of several cross-sectional return predictors is most pronounced when institutional ownership is low. Specifically, holding size fixed, stocks with low institutional ownership and high market-to-book, high analyst forecast dispersion, high turnover, or high volatility exhibit extremely low future returns, which is broadly consistent with the idea that short-sale constraints hold negative opinions off the market for these stocks. This is further underscored by the finding that prices of stocks with low institutional ownership tend to underreact to bad cash-flow news and overreact to good cash-flow news.

Direct short-sale constraints alone are unlikely to fully explain the results given the extant evidence that the costs of implementing short sales rarely exceed 1-2% per year. However, loan supply and direct costs do seem to matter at least to some extent. Return predictability effects are weaker for stocks held by Dimensional Fund Advisors, a large passive investor and active lender of stocks. This is despite the fact that these stocks are relatively small and have relatively low institutional ownership. The supply of stock loans provided by DFA seems to reduce the incidence of overpricing.

Two broad conclusions can be drawn from this work. First, the evidence in this paper supports mispricing explanations of cross-sectional return predictability. Short-sale constraints seem to go some way in explaining why sophisticated investors do not arbitrage the predictability away. The fact that direct short-selling costs are unlikely to explain the entire effect implies that short-selling of overpriced stocks in the low institutional ownership segment is a profitable trading opportunity for investors who are not subject to indirect short-sale constraints. To the extent that short selling becomes more common as increasing amounts of capital are invested in hedge funds, one might conjecture that cross-sectional return predictability effects should be less pronounced in the future.

As note of caution, it is unlikely that all cross-sectional return predictability can be traced to short-sale constraints. Clearly, even stocks with high institutional ownership still exhibit some economically significant return predictability. Moreover, during the recent burst of the technology bubble following March 2000, stocks with high market-to-book, for example, performed poorly more or less irrespective of the degree of institutional ownership. This is consistent with the arguments put forward in Brunnermeier and Nagel (2004) that sophisticated investors were actively buying highly valued stocks and that short-sale constraints were not the crucial limit to arbitrage during this period. But then again, this was an exceptional period that is perhaps unlikely to repeat soon.

Second, the results in this paper carry implications for performance measurement. Institutional managers holding high market-to-book stocks, for example, could outperform a growth stock benchmark simply because the stocks they invest in are, on average, stocks with higher institutional ownership that are less likely to be overpriced (either because there is plenty of stock loan supply or because institutional investors are ready to sell if prices go too high). Such outperformance would not reflect genuine stock selection skills. Perhaps this might explain the surprising result in Houge and Loughran (2004) that growth mutual funds perform as well as value mutual funds, even though the typical growth stock under-performs the typical value stock.

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Table 1
Summary statistics of predictor variables and firm characteristics
Panel A reports time-series averages of equal-weighted quarterly cross-sectional means and standard deviations of the return predictors used in the subsequent analysis. Log M/B is the natural logarithm of the market-to-book ratio; ADISP (analyst forecast dispersion) is the standard deviation of I/B/E/S forecasts as in Diether, Malloy, and Scherbina (2002), scaled by total assets and averaged over the previous three months; TURN (turnover) is the monthly trading volume scaled by shares outstanding, averaged over the previous three months and divided by two for Nasdaq stocks; VOL (volatility) is the standard deviation of monthly individual stock returns over the previous 12 months; RET12 (momentum) is the total individual stock return over the previous 12 months; INST is the fraction of shares outstanding held by institutional investors; Log SZ is the log of market capitalization. Panel B reports time-series averages of cross-sectional correlations. The sample period runs from the first quarter of 1980 to last quarter of 2003. Only stocks above the 20th NYSE/Amex size percentile are included.

	Log M/B	ADISP	TURN	VOL	RET12	INST	Log SZ
Panel A: Means and standard deviations							
Mean	1.00	0.01	0.07	0.13	0.11	0.34	12.45
Standard deviation	0.81	0.03	0.08	0.07	0.38	0.21	1.49
Observations per quarter (average)	2,244	1,902	3,379	3,325	3,478	3,499	3,508
Panel B: Contemporaneous correlations							
M/B		-0.01	0.04	-0.03	0.17	0.07	0.11
ADISP			0.13	0.29	-0.06	-0.13	-0.14
TURN				0.34	0.13	0.26	0.16
VOL					0.10	-0.19	-0.29
RET12						0.02	0.11
INST							0.53

Table 2
Monthly returns to portfolio strategies based on market-to-book, analyst forecast dispersion, turnover, and volatility, conditional on residual institutional ownership (RI)

At the end of each quarter *t* from September 1980 to September 2003, stocks are ranked by RI as of quarter *t*-2, obtained from the cross-sectional regressions described in the text. Stocks are sorted into five groups by RI, using quintile breakpoints. Only stocks above the 20th NYSE/Amex size percentile are included. These RI sorts are then intersected with independent quintile sorts based on quarter *t* market-to-book (Panel B), analyst forecast dispersion (Panel C), turnover (Panel D), and volatility (Panel E). Stocks are held in these portfolios for 12 months, i.e., one-fourth of each portfolio is rebalanced each quarter. The last return is from December 2003. The table presents equal-weighted returns on these portfolios with autocorrelation-consistent *t*-statistics shown in parentheses. It also reports intercepts of regressions of portfolio returns on the excess market return (CAPM α) and the three Fama-French factors (FF3F α). Returns are reported in percent per month. Panel A presents time-series averages of cross-sectional means and medians of size and institutional ownership for the five RI groups.

		Residual institutional ownership						
		(Low)				(High)		
		RI1	RI2	RI3	RI4	RI5	RI5 - RI1	(*t*-statistic)
Panel A: Firm characteristics by residual institutional ownership quintile								
Mean size (millions of dollars)		920	2243	2889	1843	706		
Median size (millions of dollars)		224	351	366	272	189		
Mean institutional ownership		0.13	0.29	0.39	0.46	0.53		
Median institutional ownership		0.10	0.29	0.41	0.47	0.54		
Panel B: Intersection with sort on market-to-book (M/B)								
P1	(Low)	1.46	1.43	1.56	1.42	1.53	0.07	(0.33)
P2		1.40	1.50	1.55	1.48	1.59	0.20	(1.04)
P3		1.10	1.30	1.33	1.41	1.41	0.31	(1.80)
P4		0.78	1.11	1.21	1.24	1.35	0.57	(3.38)
P5	(High)	-0.01	0.76	0.96	0.92	1.06	1.07	(4.91)
P1-P5	Raw	1.47	0.67	0.60	0.50	0.47	1.00	(3.80)
(*t*-statistic)		(4.07)	(2.20)	(2.15)	(1.76)	(1.58)		
P1-P5	CAPM α	1.83	0.97	0.80	0.75	0.75	1.08	(2.96)
(*t*-statistic)		(4.28)	(2.61)	(2.26)	(2.03)	(1.96)		
P1-P5	FF3F α	1.09	0.19	0.02	-0.08	-0.07	1.16	(3.58)
(*t*-statistic)		(4.13)	(0.90)	(0.11)	(0.35)	(0.27)		
Panel C: Intersection with sort on analyst forecast dispersion (ADISP)								
P1	(Low)	1.40	1.55	1.51	1.37	1.47	0.07	(0.36)
P2		1.15	1.29	1.31	1.29	1.35	0.21	(1.00)
P3		1.07	1.14	1.18	1.04	1.32	0.25	(1.54)
P4		0.87	0.93	1.08	1.05	1.19	0.31	(2.04)
P5	(High)	0.43	0.73	0.86	0.90	0.97	0.54	(2.47)

Table 2 (continued)

		Residual institutional ownership						
		(Low)				(High)		
		RI1	RI2	RI3	RI4	RI5	RI5 - RI1	(*t*-statistic)
P1-P5	Raw	0.97	0.83	0.66	0.48	0.49	0.48	(1.63)
(*t*-statistic)		(1.87)	(1.97)	(1.77)	(1.42)	(1.55)		
P1-P5	CAPM α	1.43	1.19	0.93	0.74	0.74	0.69	(1.92)
(*t*-statistic)		(2.38)	(2.34)	(2.00)	(1.76)	(1.89)		
P1-P5	FF3F α	0.74	0.56	0.33	0.23	0.24	0.50	(1.57)
(*t*-statistic)		(1.73)	(1.54)	(1.02)	(0.73)	(0.80)		
Panel D: Intersection with sort on turnover (TURN)								
P1	(Low)	1.28	1.48	1.51	1.51	1.50	0.22	(2.02)
P2		0.84	1.41	1.48	1.47	1.60	0.76	(5.26)
P3		0.64	1.21	1.28	1.33	1.44	0.79	(3.91)
P4		0.29	0.91	1.16	1.17	1.42	1.14	(3.77)
P5	(High)	0.16	0.61	0.98	1.00	1.08	0.92	(2.71)
P1-P5	Raw	1.12	0.87	0.53	0.51	0.43	0.70	(1.99)
(*t*-statistic)		(2.16)	(2.25)	(1.77)	(1.87)	(1.67)		
P1-P5	CAPM α	1.80	1.43	1.01	0.94	0.86	0.94	(2.03)
(*t*-statistic)		(3.02)	(3.25)	(3.09)	(3.26)	(2.96)		
P1-P5	FF3F α	1.00	0.82	0.51	0.51	0.45	0.54	(1.30)
(*t*-statistic)		(2.07)	(2.32)	(1.95)	(2.05)	(1.83)		
Panel E: Intersection with sort on volatility (VOL)								
P1	(Low)	1.39	1.50	1.48	1.43	1.60	0.21	(1.37)
P2		1.28	1.42	1.40	1.42	1.41	0.13	(1.02)
P3		1.00	1.28	1.31	1.29	1.42	0.42	(3.43)
P4		0.65	1.02	1.22	1.16	1.34	0.69	(3.98)
P5	(High)	0.08	0.55	0.81	0.96	1.15	1.07	(4.38)
P1-P5	Raw	1.31	0.95	0.67	0.47	0.45	0.86	(3.07)
(*t*-statistic)		(2.31)	(1.86)	(1.50)	(1.16)	(1.22)		
P1-P5	CAPM α	2.01	1.60	1.20	0.97	0.96	1.05	(2.88)
(*t*-statistic)		(3.28)	(3.01)	(2.47)	(2.25)	(2.46)		
P1-P5	FF3F α	1.36	1.05	0.70	0.52	0.59	0.77	(2.29)
(*t*-statistic)		(3.02)	(2.89)	(2.16)	(1.72)	(1.86)		

Table 3
Cross-sectional regressions are run at the end of each quarter *t* from September 1980 to December 2002, including all stocks above the 20th NYSE/Amex percentile as of quarter *t*. Dependent variable is the return over the four quarters *t*+1 to *t*+4 (in percent). Each quarter, the explanatory variables are transformed into decile ranks (before forming the interaction terms), which are then standardized to take values between zero and one. Explanatory variables are M/B, ADISP, TURN, VOL, SZ, and INST, as defined in Table 1. The table reports the time-series averages of quarterly coefficient estimates, with Fama-MacBeth-type *t*-statistics, adjusted for autocorrelation, shown in parentheses.

	Model						
Predictor variable	1	2	3	4	5	7	8
M/B	-3.85	-18.74				-5.83	-11.24
	(1.22)	(3.87)				(1.96)	(3.85)
ADISP	-4.98		-10.67			-5.54	
	(1.59)		(1.74)			(1.43)	
TURN	-3.95			-11.42		-6.49	-6.49
	(2.84)			(2.12)		(2.13)	(2.13)
VOL	-3.10				-13.35	-1.56	-4.99
	(0.96)				(1.96)	(0.37)	(0.91)
INST		-4.79	-1.18	2.62	-3.08	-2.29	-5.39
		(2.64)	(0.59)	(1.30)	(1.60)	(0.81)	(1.98)
SZ		-1.19	-2.79	-3.60	-3.18		
		(0.33)	(0.77)	(0.98)	(1.12)		
M/B x SZ		1.77					
		(0.34)					
M/B x INST		15.48				3.41	8.77
		(3.98)				(0.98)	(2.91)
ADISP x SZ			-1.24				
			(0.25)				
ADISP x INST			4.80			1.29	
			(1.25)			(0.46)	
TURN x SZ				2.32			
				(0.46)			
TURN x INST				5.90		3.61	3.05
				(1.25)		(1.18)	(1.07)
VOL x SZ					-2.14		
					(0.43)		
VOL x INST					13.06	-1.88	4.42
					(2.60)	(0.50)	(1.14)
Average R^2	7.53%	4.53%	5.18%	4.63%	5.88%	7.21%	6.74%

Table 4
Returns to portfolio strategies based on market-to-book, analyst forecast dispersion, turnover, and volatility, conditional on ownership by large stock lenders

At the end of each quarter t from July 1983 to September 2003, stocks are put into three groups: stocks held by Dimensional Fund Advisors (DFA), stocks held by the Vanguard 500 (V500) index fund, and stocks held by neither of them (others), as of quarter t-2. Only stocks above the 20th NYSE/Amex size percentile are included. These ownership sorts are then intersected with independent quintile sorts based on quarter t market-to-book (Panel B), analyst forecast dispersion (Panel C), turnover (Panel D), and volatility (Panel E). Stocks are held in these portfolios for 12 months, i.e., one-fourth of each portfolio is rebalanced each quarter. The last return is from December 2003. The table presents equal-weighted returns on these portfolios with autocorrelation-consistent t-statistics shown in parentheses. It also reports intercepts of regression of portfolio returns on the excess market return (CAPM α) and the three Fama-French factors (FF3F α). Returns are reported in percent per month. Panel A presents time-series averages of cross-sectional means and medians of size and institutional ownership for the three ownership groups.

		Ownership by			DFA - others		V500 - others	
		Others	DFA	V500	mean	(t-statistic)	mean	(t-statistic)
Panel A: Firm characteristics by Ownership Group								
Mean size (millions of dollars)		746	342	9826				
Median size (millions of dollars)		284	168	4114				
Mean instititutional ownership		0.31	0.34	0.55				
Median institutional ownership		0.27	0.32	0.56				
Panel B: Intersection with sort on market-to-book (M/B)								
P1	(Low)	1.26	1.32	1.51	0.07	(0.47)	0.25	(1.32)
P2		1.34	1.39	1.36	0.05	(0.49)	0.02	(0.15)
P3		1.12	1.20	1.26	0.08	(0.83)	0.14	(0.99)
P4		0.87	1.11	1.16	0.24	(1.82)	0.29	(1.76)
P5	(High)	0.19	0.64	1.03	0.45	(3.54)	0.85	(2.60)
P1-P5	Raw	1.07	0.69	0.47	0.38	(2.34)	0.60	(2.11)
(t-statistic)		(3.04)	(1.88)	(1.64)				
P1-P5	CAPM α	1.39	1.02	0.54	0.37	(1.59)	0.85	(2.53)
(t-statistic)		(3.39)	(2.23)	(1.38)				
P1-P5	FF3F α	0.72	0.21	-0.14	0.51	(2.15)	0.87	(2.87)
(t-statistic)		(2.86)	(0.81)	(0.60)				
Panel C: Intersection with sort on analyst forecast dispersion (ADISP)								
P1	(Low)	1.35	1.29	1.34	-0.06	(0.56)	-0.02	(0.14)
P2		1.02	1.18	1.21	0.16	(1.56)	0.19	(1.75)
P3		0.88	1.03	1.09	0.15	(1.32)	0.21	(1.43)
P4		0.71	0.93	0.97	0.21	(1.75)	0.26	(1.69)
P5	(High)	0.38	0.74	0.80	0.36	(2.06)	0.42	(1.45)

Table 4 (continued)

		Ownership by			DFA - others		V500 - others	
		Others	DFA	V500	mean	(*t*-statistic)	mean	(*t*-statistic)
P1-P5	Raw	0.97	0.56	0.53	0.41	(2.07)	0.44	(1.42)
(*t*-statistic)		(1.92)	(1.26)	(1.46)				
P1-P5	CAPM α	1.39	0.91	0.80	0.48	(1.79)	0.59	(1.44)
(*t*-statistic)		(2.28)	(1.73)	(1.71)				
P1-P5	FF3F α	0.62	0.28	0.38	0.34	(1.27)	0.24	(0.66)
(*t*-statistic)		(1.39)	(0.75)	(0.95)				
Panel D: Intersection with sort on turnover (TURN)								
P1	(Low)	1.10	1.38	1.34	0.27	(2.67)	0.23	(0.87)
P2		0.86	1.40	1.24	0.54	(3.86)	0.38	(1.50)
P3		0.67	1.27	1.37	0.60	(4.35)	0.70	(2.87)
P4		0.67	0.97	1.21	0.30	(1.72)	0.53	(1.88)
P5	(High)	0.21	0.66	1.31	0.45	(3.52)	1.11	(3.88)
P1-P5	Raw	0.90	0.72	-0.02	0.18	(1.37)	0.87	(2.70)
(*t*-statistic)		(2.12)	(1.89)	(0.06)				
P1-P5	CAPM α	1.53	1.31	0.40	0.22	(1.11)	1.13	(2.46)
(*t*-statistic)		(3.19)	(3.05)	(0.86)				
P1-P5	FF3F α	0.79	0.67	0.12	0.12	(0.66)	0.67	(1.63)
(*t*-statistic)		(2.33)	(2.18)	(0.27)				
Panel E: Intersection with sort on volatility (VOL)								
P1	(Low)	1.40	1.38	1.29	-0.02	(0.28)	-0.12	(0.85)
P2		1.22	1.27	1.26	0.06	(0.67)	0.04	(0.32)
P3		1.00	1.13	1.24	0.13	(1.66)	0.25	(1.84)
P4		0.61	1.10	1.15	0.49	(4.51)	0.54	(2.46)
P5	(High)	0.01	0.81	1.19	0.80	(5.20)	1.18	(2.83)
P1-P5	Raw	1.39	0.57	0.09	0.82	(4.91)	1.30	(3.15)
(*t*-statistic)		(2.36)	(1.11)	(0.16)				
P1-P5	CAPM α	2.07	1.20	0.66	0.87	(3.87)	1.41	(2.60)
(*t*-statistic)		(3.24)	(2.20)	(0.97)				
P1-P5	FF3F α	1.35	0.60	0.30	0.74	(3.32)	1.05	(1.98)
(*t*-statistic)		(2.98)	(1.62)	(0.49)				

Table 5
Reaction to cash-flow news conditional on residual institutional ownership
Panel A reports the vector autoregression (VAR) parameter estimates from quarterly cross-sectional regressions. Each quarter from 1981 to 2003, the firm-level state variables *ret12* (log 12-month stock return), roe^{CS} (log clean-surplus return on equity), roe^{GAAP} (log GAAP return on equity), and *b-m* (log book-to-market ratio) are regressed on the state variable vector lagged by four quarters. The time-series averages of these quarterly estimates are used as the estimate for the VAR transition matrix. Cross- and autocorrelation-consistent Fama-MacBeth-type standard errors reported in brackets are obtained from the time-series variation of the coefficient estimates with a Newey-West adjustment. In Panel B, stocks are sorted at the end of each quarter *t* into portfolios based on residual institutional ownership as of quarter *t*-5 and cash-flow news, where cash-flow news is calculated indirectly, as the sum of unexpected log return and expected return news over the period from quarter *t*-4 to *t*-1. In Panel C, stocks are sorted by directly calculated cash-flow news, that is, the discounted sum of changes in expected future clean-surplus return on equity. Stocks are held in these portfolios for 12 months, i.e., one-fourth of each portfolio is rebalanced each quarter. Panels B and C show equal-weighted returns on these portfolios with *t*-statistics in parentheses. Returns are reported in percent per month. All results are obtained using stocks above the 20th NYSE/Amex size percentile as of quarter *t*-5. The sample period for portfolio returns runs from April 1981 to December 2003.

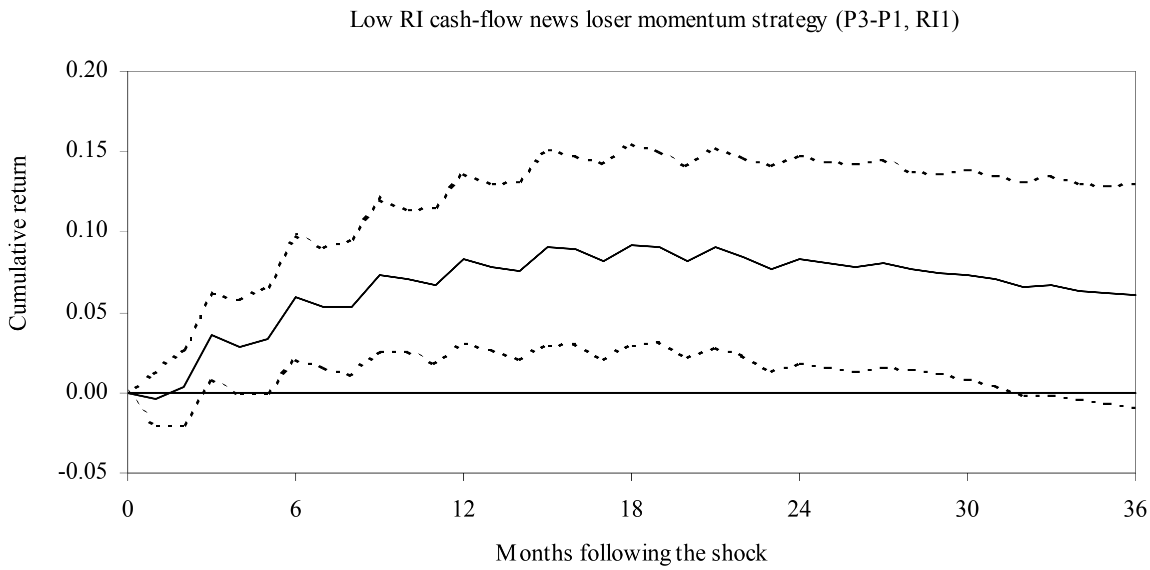
Panel A: Estimated VAR transition matrix

Variable	$ret12_{t-1}$	roe_{t-1}^{CS}	roe_{t-1}^{GAAP}	$b\text{-}m_{t-1}$
$ret12_t$	0.061	-0.033	0.112	0.067
	[0.031]	[0.012]	[0.014]	[0.021]
roe_t^{CS}	0.125	-0.005	0.228	-0.078
	[0.013]	[0.015]	[0.020]	[0.007]
roe_t^{GAAP}	0.089	0.009	0.549	0.026
	[0.011]	[0.014]	[0.017]	[0.010]
$b\text{-}m_t$	0.074	-0.043	0.042	0.836
	[0.024]	[0.012]	[0.012]	[0.017]

	Residual institutional ownership						
	(Low) RI1	RI2	RI3	RI4	(High) RI5	RI5 - RI1	(*t*-statistic)
Panel B: Sort on cash-flow news obtained from the VAR (indirect method)							
P1 (Low)	0.23	0.57	0.76	0.76	0.76	0.53	(2.29)
P2	0.94	1.11	0.98	1.01	1.05	0.11	(0.76)
P3	1.16	1.20	1.16	1.15	1.15	-0.01	(0.06)
P4	1.18	1.26	1.12	1.07	1.27	0.09	(0.58)
P5 (High)	0.70	1.02	1.13	1.12	1.26	0.56	(3.32)
P5-P1	0.47	0.44	0.37	0.37	0.50	0.03	(0.12)
(*t*-statistic)	(1.27)	(1.26)	(1.24)	(1.23)	(1.73)		
P3-P1 (Loser Momentum)	0.93	0.63	0.40	0.39	0.39	-0.54	(2.09)
(*t*-statistic)	(2.30)	(1.78)	(1.41)	(1.37)	(1.53)		
P5-P3 (Winner Momentum)	-0.46	-0.18	-0.04	-0.03	0.10	0.57	(3.44)
(*t*-statistic)	(1.62)	(0.78)	(0.19)	(0.15)	(0.49)		

Table 5 (continued)

	Residual institutional ownership						
	(Low) RI1	RI2	RI3	RI4	(High) RI5	RI5 - RI1	(*t*-statistic)
Panel C: Sort on cash-flow news obtained from the VAR (direct method)							
P1 (Low)	0.03	0.45	0.69	0.60	0.73	0.70	(3.06)
P2	1.02	1.10	1.03	0.98	1.10	0.08	(0.52)
P3	1.21	1.19	1.15	1.18	1.25	0.03	(0.21)
P4	1.14	1.28	1.14	1.17	1.31	0.17	(1.01)
P5 (High)	0.64	1.03	1.05	1.14	1.29	0.65	(3.72)
P5-P1	0.61	0.58	0.36	0.54	0.56	-0.05	(0.21)
(*t*-statistic)	(1.83)	(1.83)	(1.32)	(2.07)	(2.09)		
P3-P1 (Loser Momentum)	1.18	0.74	0.46	0.58	0.52	-0.66	(2.59)
(*t*-statistic)	(2.93)	(2.17)	(1.55)	(2.09)	(2.15)		
P5-P3 (Winner Momentum)	-0.58	-0.16	-0.10	-0.03	0.04	0.61	(3.47)
(*t*-statistic)	(2.08)	(0.78)	(0.52)	(0.21)	(0.22)		



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Be sure to use dashed lines, as the author refers to them in the text

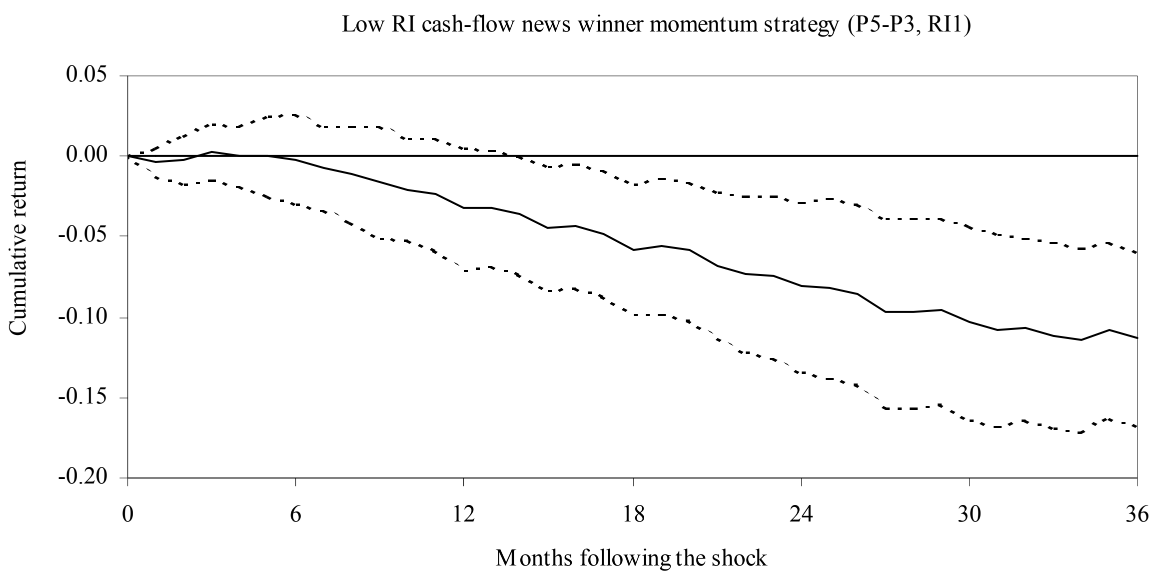

Fig. 1. Reaction to cash-flow news of stocks with low residual institutional ownership (RI).
This figure shows long-run cumulative returns on the cash-flow news loser momentum strategy in the low residual ownership segment (P3-P1, RI1), presented in the top graph, and the cash-flow news winner momentum strategy (P5-P3, RI1), presented in the bottom graph. Portfolios are formed as in Table 5, Panel B. Cash-flow news is based on the vector autoregression from Table 5, calculated indirectly as the sum of unexpected return and expected return news over the 12 months prior to portfolio formation. Returns are cumulated over holding periods ranging from one to 36 months. The dashed lines denote +/- 2 standard error bands. The sample period runs from April 1981 to December 2003.