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Who Underreacts to Cash-Flow News? Evidence from Trading between Individuals and Institutions[†]

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Who Underreacts to Cash-Flow News?
Evidence from Trading between Individuals and Institutions

Abstract

A large body of literature suggests that firm-level stock prices "underreact" to news about future cash flows. We estimate a vector autoregession to examine the joint behavior of returns, cash-flow news, and trading between individuals and institutions. Our main finding is that institutions buy shares from individuals in response to good cash-flow news, thus exploiting the underreaction phenomenon. Institutions are not simply following price momentum strategies: When price goes up in the absence of positive cash-flow news, institutions sell shares to individuals. The response of institutional ownership to cash-flow news is weaker for small stocks. Since small stocks also exhibit the strongest underreaction patterns, this finding is consistent with institutions facing exogenous constraints in trading small stocks.

Keywords: underreaction, overreaction, cash-flow news, expected returns, individuals, institutions, trading

JEL classification codes: G120, G140

An emerging body of empirical literature suggests that stock prices "underreact" to new information about firms' cash flows. Events that are a priori likely to contain cash-flow-relevant information, such as earnings surprises and dividend initiations and omissions, are followed by a stock price drift in the same direction as the initial announcement return.[1] While some researchers (e.g., Fama [1998]) argue that these empirical findings are sample-specific chance results, others have tried to devise models to explain them (Barberis, Shleifer, and Vishny [1998], Daniel, Hirshleifer, and Subrahmanyam [1998], and Hong and Stein [1999]).

This paper uses a highly stylized vector autoregression (VAR) to offer additional evidence on investor heterogeneity and underreaction. By definition, a firm's stock returns are driven by shocks to expected cash flows (i.e., cash-flow news) and/or shocks to discount rates (i.e., expected-return news). Vuolteenaho's (2001b) VAR results show that the immediate price response to cash-flow news is less than one-for-one, consistent with underreaction found in many event studies. Our contribution is to measure the response of institutional ownership to cash-flow and expected-return news.

Our main findings are easily summarized. First, institutions respond to positive cash-flow news by buying shares from individual investors, thus exploiting the underreaction pattern. According to the VAR, 25% cash-flow news results in institutions buying approximately 2% of the shares outstanding. Considering that the average stock has a cash-flow-news standard deviation of 47% and institutional ownership of 36%, this response is economically significant. Second, we find that institutions are not simply following price-momentum strategies. When the stock price increases 25% in the absence of cash-flow news, institutions sell approximately 5% of the shares outstanding to individuals. Third, the response of institutional ownership to cash-flow news is weaker for small stocks. Since small stocks also exhibit the strongest underreaction patterns, this finding is consistent with institutions facing exogenous constraints in trading small stocks.

A large body of empirical literature investigates the investment behavior of institutions, and our paper adds to this evidence. First, Lakonishok, Shleifer, and Vishny (1992), Grinblatt, Titman, and Wermers (1995), Wermers (1999), Nofsinger and Sias (1999), Grinblatt and Keloharju (2000a, b), and others show that institutional buying and stock returns are contemporaneously correlated. Our paper qualifies this result further by showing that only the permanent component of return (i.e., cash-flow news) is positively correlated with institutional buying. Second, Daniel, Grinblatt, Titman, and Wermers (1997), Wermers

(1999), Nofsinger and Sias (1999), Grinblatt and Keloharju (2000a, b), and others find evidence that the short-term expected returns are higher (lower) for stocks that have recently been subject to significant institutional buying (selling). By using the present-value framework and a VAR, we extend these return-predictability findings to statements about the level of the prices. Third, Del Guercio (1996), Falkenstein (1996), Gompers and Metrick (2000), and others document institutional preferences for certain types of security and/or firm characteristics. The VAR model of this paper provides a tool for describing the short-run and long-run dynamics of these preferences and their relation to the price-formation process.

Our results also have relevance to theories hypothesizing that institutional investors follow destabilizing positive-feedback trading strategies (Lakonishok, Shleifer, and Vishny [1992] and others). According to our findings, cash-flow news is the component of contemporaneous return that is positively correlated with institutional buying. Under the plausible assumption that cash-flow news is exogenous (i.e., returns and/or ownership structure do not cause the expected cash flows), this buying cannot feed back in a destabilizing way. The positive correlation of institutional ownership and expected-return news also suggests that institutions do not follow positive-feedback investment strategies, although one cannot directly infer causality from this correlation.

Finally, our cross-sectional analysis is largely in agreement with Cohen's (2000) time-series analysis. Cohen examines the aggregate institutional and individual portfolio stock-bond allocations and shows that institutions tend to buy stocks from individuals when expected returns go up. Like Cohen's, our results suggest that to the extent that the aggregate trading of institutions affects asset prices, these effects are unlikely to be deleterious to the efficient functioning of the capital markets. On the contrary, institutional trades appear to reduce the cross-sectional differences between the long-run expected returns on different stocks, thus should not tend to be destabilizing.

The rest of the paper is organized as follows. Section I outlines the VAR methodology of measuring underreaction. Section II shows how price and institutional ownership respond to cash-flow news. Section III shows the results of additional robustness checks. Section IV concludes.

I. Measuring underreaction to cash-flow news

We measure over- and underreaction to cash-flow news using Campbell's (1991) return-decomposition methodology. We use a VAR to empirically decompose the unexpected stock return into two components: cash-flow and expected-return news. Within this decomposition, cash-flow news is the return that would have realized if expected returns had not changed. Our measure of over- and underreaction is the regression coefficient of realized stock return on contemporaneous cash-flow news. A regression coefficient greater than unity corresponds to overreaction and a coefficient less than unity to underreaction.

A. Return-decomposition framework

Campbell (1991), Vuolteenaho (2001b), and others decompose the unexpected stock return into an expected-return component and a cash-flow component:

$$r_t - E_{t-1} r_t = \Delta E_t \sum_{j=0}^{\infty} \rho^j e_{t+j} - \Delta E_t \sum_{j=1}^{\infty} \rho^j r_{t+j} + \kappa_t \,, \tag{1}$$

where ΔE_t denotes the change in expectations from $t-1$ to t (i.e., $E_t(\cdot) - E_{t-1}(\cdot)$), e_t the log accounting return on equity (ROE), r_t the log stock return, and κ the approximation error. ρ is a constant set to 0.97. (The details of the derivation of equation [1] and the choice of ρ are reproduced in Appendix 1.) We defining the two return components as cash-flow news (N_{cf}) and expected-return news (N_r):

$$N_{cf,t} \equiv \Delta E_t \sum_{j=0}^{\infty} \rho^j e_{t+j} + \kappa_t, \quad N_{r,t} \equiv \Delta E_t \sum_{j=1}^{\infty} \rho^j r_{t+j} \,. \tag{2}$$

Since $r_t - E_{t-1} r_t = N_{cf,t} - N_{r,t}$, the unexpected stock return can be high if either expected returns decrease and/or expected future ROEs increase.[2] When price goes up, the price increase must either be followed by high cash flows or the price must come back down. If expected returns remain constant, unexpected return equals cash-flow news.

Campbell's (1991) return decomposition is related to the Beveridge-Nelson (1981) decomposition in the time-series literature. The Beveridge-Nelson decomposition separates a time series into two additive components, a random walk and a stationary component. If ρ is set to 1 in equation (2), cash-flow news corresponds to the shock to the random-walk component of the log stock price and expected-return news to the shock to the stationary component of the log stock price. According to this interpretation, the cash-flow news is a shock to the long-run "price-target trend" that the stock price is expected to approach.

An adaptation of the familiar present-value formula can be used to illustrate the intuition behind this return decomposition. According to the present-value formula in equation (3), an asset's price equals the discounted present value of its expected future cash flows plus a pricing error:

$$P_{t-1} = \sum_{i=0}^{\infty} \left\{ \frac{E_{t-1}(CF_{t+i})}{\prod_{j=0}^{i}(1+K_{t+j})} \right\} + \varepsilon_{t-1}, \tag{3}$$

where P denotes price, CF cash flow, K discount rate, and ε pricing error. Clearly, the price can increase if expected cash flows increase and/or discount rates decrease and/or the pricing error increases. In Campbell's (1991) return decomposition, cash-flow news corresponds approximately to the percentage price change due to the change in expected cash flows, or the return that would have realized if the discount rates and pricing error had not changed. Expected-return news is the percentage price change due to changes in discount rates and/or in the pricing error.

Of course, Campbell's (1991) return decomposition is a purely mechanical construct and requires minimal assumptions about the behavior of the market participants. Typically, the return and ROE expectations in equations (1) and (2) must be estimated from the data and will, therefore, reflect the econometrician's method of forming these expectations. Interpretation of the estimated news terms requires more assumptions. As the first set of working assumptions, we assume that the VAR process correctly describes the evolution of rationally formed conditional expectations and that the fair discount rates are constant across stocks (but not over time). Under these assumptions, the estimated market-adjusted expected-return-news series reflects biases in the market's pricing process and would perhaps better be labeled as "mispricing news."

B. Defining underreaction

Following Vuolteenaho (2001b), we define overreaction to cash-flow news in terms of a simple regression coefficient. We make two working assumptions: First, we assume that, at any point of time, the "fair" discount rates are equal across all stocks. This assumption enables us to identify market-adjusted expected-return news as solely due to changes in the pricing error. Second, we assume that cash-flow news is exogenous, i.e., that the discount rates and/or pricing error do not cause cash-flow news.

Under these assumptions, one can raise the question whether the market's reaction to the relevant cash-flow news is excessive, correct, or insufficient. We define the overreaction as $b > 1$ in the following regression:

$$\tilde{r}_t = a + b\,\tilde{N}_{cf,t} + w_t. \tag{4}$$

Conversely, the underreaction case corresponds to $b < 1$ and the correct reaction case to $b = 1$. In words, if good cash-flow news typically results in the stock becoming more overpriced (or less underpriced,) we call this overreaction. Conversely, if good cash-flow news on average results in less overpriced (or more underpriced) stock, we call this underreaction.

For example, consider a stock worth $100. If there is news that all expected cash flows are 15% higher (while holding the risk and fair discount rates constant), an unbiased or correct stock-price reaction is 15% return and $115 stock price (assuming no dividends). If the stock return and price responses to such news are typically 10% and $110, $b < 1$ and it is reasonable to call this price behavior underreaction.

Our seemingly convoluted definition of over- and underreaction differs from the definitions adopted by a typical empirical study. For example, DeBondt and Thaler (1985) examine the univariate autocovariance function of returns and infer overreaction from long-horizon negative autocorrelation. However, our definition of over- and underreaction has the following advantages over the univariate approach. First, as noted by Campbell (1991) and Vuolteenaho (2001b), a univariate time-series approach cannot unambiguously estimate both the variance of expected-return news and the regression coefficient of return on cash-flow news. It is possible that the price responds less than one-for-one to cash-flow news, yet returns are negatively autocorrelated. This is because the long-horizon negative autocorrelation may be induced to returns by any type of mispricing, including pure noise, not only by overreaction. Second, our definition is capable of separating underreaction from delayed overreaction. If the price initially overreacts ($b > 1$) but this overreaction is followed by future price movements in the same direction, many alternative approaches incorrectly classify this pattern as underreaction.

C. VAR implementation

A vector autoregression (VAR) provides a convenient way to implement the return decompositions. Let $z_{i,t}$ be a vector of firm-specific state variables describing a firm *i* at time *t*. In particular, let the first element of $z_{i,t}$ be the firm's market-adjusted log stock return. An individual firm's state vector is assumed to follow a linear law:

$$z_{i,t} = \Gamma\, z_{i,t-1} + u_{i,t}\,. \tag{5}$$

The VAR coefficient matrix Γ is assumed to be constant, both over time and across firms. The error term $u_{i,t}$ is assumed to have a covariance matrix Σ and to be independent of everything known at $t-1$. At this stage, we make no assumptions on how the errors are correlated across firms. The model is homogenous over firms – a firm is expected to behave similarly to others with the same values of the state variables. Because the error terms are not necessarily perfectly correlated across firms, however, two firms that are equal today do not have to be equal tomorrow.

The VAR implies a return decomposition. Define $e1' \equiv [1 \quad 0 \quad \cdots \quad 0]$ and

$$\lambda' \equiv e1' \rho \Gamma (I - \rho \Gamma)^{-1} \tag{6}$$

The definition (6) introduced by Campbell (1991) simplifies the expressions considerably: Expected-return news can then be conveniently expressed as $\lambda' u_{i,t}$ and cash-flow news as $(e1' + \lambda') u_{i,t}$. If returns are unpredictable, i.e., the first row of Γ is zeros, expected-return news is identically zero and the entire return is due to cash-flow news.

Effectively, Campbell's (1991) method first computes expected-return news directly and then backs out the cash-flow news as unexpected return plus expected-return news. It may seem that this indirect method of calculating cash-flow news as a residual relies on heavier assumptions than does directly calculating the change in the discounted sum of clean-surplus ROEs. The robustness-checks section uses the clean-surplus ROE directly and shows that the results are robust to the choice between these two alternatives. Also, setting ρ equal to 1, which results in cash-flow news being equal to the shock to the permanent component of the log stock price and expected-return news being equal to the shock to the temporary component of the log stock price, does not alter our stated results.

Finally, our measure of over- and underreaction, the regression coefficient of the total stock return on cash-flow news, can be computed from the VAR parameters using a simple formula: $1 - \lambda' \Sigma (e1 + \lambda) / [(e1' + \lambda') \Sigma (e1 + \lambda)]$. This formula is derived by recognizing that the total return equals conditional expected return plus cash-flow news less expected-return news and that the conditional expected return is independent of the news terms.

II. Empirical results

A. The VAR specification

We estimate a homogenous VAR from a firm-level panel (the CRSP-COMPUSTAT intersection linked to the SPECTRUM database of institutional holdings). Our final sample covers the period 1983-1998 (16 years) and consists of 23,501 firm-years. Table I and Figure 1 show descriptive statistics and Appendix 2 contains the details of data sources and variable definitions.

We consider a parsimonious VAR specification that uses market-adjusted log stock return, log book-to-market, log GAAP ROE, and fraction of institutional ownership as the state variables. Only one lag of each is used to predict the state vector evolution. This four-variable VAR specification is designed to capture the following empirical return-predictability results. Historically, past long-term losers have outperformed past long-term winners ("long-term reversal," DeBondt and Thaler [1985]), while past short-term winners have outperformed past short-term losers ("momentum," Jegadeesh and Titman [1993]). High book-to-market-equity firms have earned higher average stock returns than low book-to-market-equity firms ("book-to-market anomaly," Rosenberg, Reid, and Lanstein [1985] and others). Controlling for other characteristics, firms with higher profitability have earned higher average stock returns (Haugen and Baker [1996]). Finally, institutional ownership predicts one-period returns (Wermers [1999] and others). The results of Vuolteenaho (2001b) suggest that a similar simple specification adequately captures the features of the data that are important to the computation of the news terms. Consistent with this finding, we document in the robustness-checks section that our main results are not sensitive to changes in the VAR specification.

We use robust and simple methods – the weighted least squares (WLS) approach and one pooled prediction regression per state variable – in estimating the VAR parameters. Instead of using the optimal but unknown GLS weights or unit OLS weights, we weigh each cross-section equally, much as the Fama-MacBeth (1973) procedure does. In practice, this means deflating the data for each firm-year by the number of firms in the corresponding cross-section. (The main findings of the paper are not sensitive to the choice between pooled OLS, pooled WLS, or Fama-MacBeth procedures.) We use two methods to calculate cross-correlation-consistent standard errors: Rogers' (1983, 1993) robust standard-error method and Shao and Rao's (1993) jackknife method. (Vuolteenaho [2001b] discusses the details of these procedures.)

The parameter estimates (presented in Table II) imply that expected returns are high when past one-year return, the book-to-market ratio, profitability, and institutional ownership are high. Expected profitability is high when past stock return and past profitability are high and the book-to-market ratio low. Our result that institutional ownership predicts returns after controlling for other stock characteristics is consistent with the empirical results of Wermers (1999), Gompers and Metrick (2000), Pirinsky (2000), and others. In summary, our VAR parameter estimates are of sign and magnitude consistent with previous research.

B. Responses of price and institutional ownership to cash-flow news

Panel A of Table III shows the variance decomposition of unexpected returns computed using the following formulas:

$$\begin{aligned} \operatorname{var}(N_r) &= \lambda'\Sigma\lambda \\ \operatorname{var}(N_{cf}) &= (e1' + \lambda')\Sigma(e1 + \lambda) \\ \operatorname{cov}(N_r, N_{cf}) &= \lambda'\Sigma(e1 + \lambda) \end{aligned} \tag{7}$$

Consistent with Vuolteenaho (2001b), cash-flow news is the main driver of firm-level stock returns. The expected-return-news standard deviation is 25% (variance 0.0619 with 0.0208 standard error) and the cash-flow-news standard deviation is 47% (variance 0.2182 with 0.0379 standard error). The correlation between the two news series is 0.77 and more than ten standard errors from zero (under the assumption that the VAR model is correctly specified.) Interestingly, the shock to institutional ownership is positively correlated with cash-flow news (correlation 0.38) and expected-return news (correlation 0.49). That is, when long-horizon expected returns and cash flows increase, the institutions buy shares from individuals.

Panel C of Table III shows the estimated regression coefficient of stock return on cash-flow news, 0.58. This regression coefficient shows how much the price moves on average if there is $1 cash-flow news. As discussed in Section I.B, our interpretation of this regression coefficient is that the market underreacts to $1 cash-flow news by 42 cents. Since our estimation method weighs all stocks equally, these underreaction results are best interpreted as applying to a typical small or medium-capitalization stock.

Figure 2 further illustrates some of the dynamics implied by the estimated VAR. The top graph of Figure 2 shows the cumulative response of returns to 25% cash-flow news. If expected returns were constant, this shock would result in exactly 25% realized unexpected return. Instead, the initial response is only 15%, consistent with the above-documented underreaction phenomenon. A notable feature of the impulse response is the absence of any delayed overreaction: Instead of overshooting, the price slowly converges to the new level. The bottom graph of Figure 2 also shows the cumulative response of returns to a 25% return in the absence of any cash-flow news. After the shock, the price decays for a decade, eventually reversing the entire 25% return. These impulse-response functions are largely consistent with those estimated by Vuolteenaho (2001b) from a longer 1954-1996 sample.

In addition to documenting the above underreaction pattern, we examine how the ownership structure responds to cash-flow news and high subsequent expected returns. Panel C of Table III also shows the estimated regression coefficient of institutional-ownership shock on cash-flow news, 0.08. This regression coefficient shows how large a fraction of the firm institutions buy on average if there is 100% cash-flow news. Since the regression coefficient is reliably positive (t-statistic 8.9), we conclude that institutions buy on positive cash-flow news. The magnitude of the coefficient is economically significant: one-standard-error cash-flow news results in 4% of the firm changing hands between the aggregate groups of individuals and institutions.

Analogously to Figure 2, Figure 3 illustrates the trading dynamics implied by the VAR. The top graph of Figure 3 shows the response of institutional ownership to 25% cash-flow news. Contemporaneously with the cash-flow news, institutions buy over 2% of the firm and continue to overweigh it for several years.

The above finding that institutions buy on good news and sell on bad news is consistent with the institutions following a simple price-momentum strategy. However, the bottom graph of Figure 3 shows that this is unlikely to be the case. Analogously to the bottom graph of Figure 2, we shock the VAR with a 25% return in the absence of any cash-flow news. During such price run-ups that are unrelated to cash-flow news, institutions sell to individuals and under-weigh the stock in their portfolios for years. This effect, too, is economically significant. The standard deviation of expected-return news that is not explained by cash-flow news is approximately 16% and one-standard-error move in this residual on average coincides with individuals and institutions changing their aggregate positions by 3% of the shares outstanding.

We also measure the extent to which patterns in institutional portfolio allocations coincide with patterns in expected returns. To examine whether institutions in aggregate take positions proportional to expected returns, we compute the correlation between short- and long-term expected returns and the level of institutional ownership. The one-period expected return is computed simply as the fitted value from the first VAR prediction equation. The measure of long-horizon expected return we adopt is the "atypical discount," p_r, as defined by Vuolteenaho (2001a):

$$p_{r,t-1} \equiv \sum_{j=0}^{\infty} \rho^j (E_{t-1} r_{t+j} - \bar{r}) \,. \tag{8}$$

Above, $\bar{r} \equiv E(r)$ denotes the normal or typical log risk premium or discount rate.[3] As seen from equation (8), atypical discount is the cumulative effect of return predictability on prices. If a stock's atypical discount is high, the expected future returns on this stock are also high and the stock price is low (relative to the expected cash flows). The market-adjusted atypical discount, $\tilde{p}_{r,t-1} \equiv \sum_{j=0}^{\infty} \rho^j E_{t-1} \tilde{r}_{t+j}$, can be conveniently computed from the VAR model using the formula $\rho^{-1}\lambda'(z_{t-1} - \bar{z})$, where $\bar{z}$ denotes the mean state vector.

Panel B of Table III shows the covariance and correlation matrices of one-period expected return, long-horizon expected return (p_r), and the fraction of institutional ownership. The correlation between one-period expected returns and the level of institutional ownership is 0.41 with a 0.06 standard error. The correlation between long-horizon expected returns (p_r) and the level of institutional ownership is somewhat stronger at 0.64 with a 0.09 standard error. If one were to assign the causality from long-horizon expected returns to institutional ownership and regress the ownership fraction on long-horizon expected returns, this regression would explain 41% of the variation in institutional ownership.

Our main results are largely consistent with institutions truly understanding the return-generating process and using this understanding to make smart bets. However, our findings are also consistent with institutions following rules of thumb motivated by some completely unrelated factors, and these rules of thumb being positively correlated with expected returns. To some extent, this distinction is moot. As argued by Milton Friedman (1953), while modeling a skilled pool player as literally calculating exactly how hard and at what angle to hit the ball is certainly an unrealistic description of reality, such a model may be a very good predictor of much more complicated reality and thus a useful way to think about a skilled pool player. Similarly, the exact mechanism of institutional investment decision making may be based on a complicated set of heuristics, yet it may be adequately modeled as rational-expectations maximization.

It is also interesting to relate the patterns in cash-flow news, expected returns, and institutional ownership to recent theoretical models by Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). Daniel, Hirshleifer, and Subrahmanyam (1998) design a model that relies on investor overconfidence. In addition, this overconfidence varies through time. The central predictions of Daniel, Hirshleifer, and Subrahmanyam's (1998) model are that "stock prices overreact to private information signals and underreact to public signals." In a model by Hong and Stein (1999), the over- and underreaction patterns are due to the interaction between two groups of boundedly rational traders. In addition to the predictions about the impulse-response functions for a typical stock, the Hong and Stein (1999) model has cross-sectional predictions. The Hong and Stein (1999) model predicts that stocks for which information diffuses more slowly exhibit more underreaction to private information than stocks for which information diffuses quickly. Since the state variables in our model are clearly not private information, we cautiously speculate that our results may be consistent with these models.

Finally, of course, our results may also be consistent with a risk story. Good cash-flow news may be correlated with an increase in (yet unspecified) risk. Such an increase in risk would be somewhat counterintuitive, as the typical distress or leverage intuition would suggest that good cash-flow news coincide with a decrease in risk. Nevertheless, one cannot completely rule out the possibility of risk as an explanation to the high expected returns subsequent to positive cash-flow news.

C. Size patterns in underreaction and trading

Previous research shows that the underreaction pattern varies as a function of the firm's characteristics. We first measure this size pattern in underreaction and then contrast it to the pattern in trading between individuals and institutions.

One way to allow for cross-sectional variation in underreaction pattern is to let the VAR-error covariance matrix Σ vary across firms while assuming that the VAR coefficient matrix Γ is common for all stocks. In Table IV Panel A and Figure 4 (top two graphs), we sort stocks into quintiles based on firm size (i.e., market value of equity) and estimate a separate underreaction coefficient for each group. In this sample, the regression coefficient of return on cash-flow news varies as a function of firm size. For the smallest quintile of stocks in our sample, the coefficient is 0.55, corresponding to a 45-cent underreaction to one-dollar cash-flow news. For the largest stocks, the regressions coefficient is significantly higher: 0.67 or 33-cent underreaction to one-dollar cash-flow news. The difference in coefficients between the two extreme quintiles is 0.10, two-and-half standard errors from zero.

Because we constrain the transition matrix to be equal across size groups, the size-related heterogeneity in the underreaction pattern might be an artifact of this restriction. To investigate this possibility, we estimate a separate transition matrix for each size quintile and assume that each firm's assignment to a size quintile is permanent. The results obtained under these assumptions (presented in Table IV Panel B and Figure 4 [bottom two graphs]) show an even stronger size pattern in underreaction. As above, the stocks in the smallest quintile have a return-on-cash-flow-news coefficient of 0.56, corresponding to a 44-cent underreaction to one-dollar cash-flow news. For the largest stocks, allowing the transition matrix to vary as a function of size changes the results significantly: the estimated coefficient is

1.01, or almost exactly correct reaction to cash-flow news. The difference in coefficients between the two extreme quintiles is –0.45, almost four standard errors from zero.

Also the regression coefficient of institutional-ownership shock on cash-flow news varies as a function of firm size. In Table IV Panel A, stocks in all quintiles are assumed to share the same transition matrix, but the error covariance matrix is allowed to vary across the quintiles. For the smallest quintile, the coefficient is 0.0455, and for the largest quintile 0.1375. The difference in coefficients between the two extreme quintiles is -0.0920 with a 0.0139 standard error. Table IV Panel B uses slightly different assumptions: We assume that the size-group assignment is permanent and estimate a separate transition matrix and error covariance matrix for stocks in each size quintile. The point estimates have a lower precision but are generally consistent with the above-mentioned results obtained under different assumptions.

These results raise the question why institutional investors do not respond more aggressively to the cash-flow-news underreaction of small stocks, exploiting the larger opportunities. One hypothesis is that many institutions face various constraints in trading small stocks, or that they simply prefer to trade large stocks. This hypothesis is supported by Falkenstein (1996), Gompers and Metrick (2000), and others who find that institutions prefer to hold large, liquid stocks. These authors suggest that the large positions held by institutions may lead them to demand stocks with large market capitalizations and thick markets. For example, if institutions turn over their portfolios and trade more often than individuals do (Schwartz and Shapiro [1992]), then they would be more sensitive to the transactions costs caused by large-percentage bid-ask spreads for illiquid or low-priced stocks. In addition, many institutions are explicitly or implicitly constrained to only invest in stocks that are heavily weighted in a particular benchmark index, such as S&P 500 (Shleifer [1986], Harris and Gurel [1986], Beneish and Whaley [1996], Lynch and Mendenhall [1997], and others). These often self-imposed constraints may stem from various agency considerations. Finally, costly SEC reporting requirements for investors that hold more than five percent of a firm's stock may lead to some institutional avoidance of small firms.

If institutions indeed face constraints in taking small-stock positions, the institutional trading patterns may offer an explanation to the cross-sectional underreaction patterns. If individuals underreact more than institutions, their underreaction is likely to impact the prices more in markets where institutional trading is constrained, such as small stocks. However, because market value of equity is endogenous and correlated with many other observable and unobservable variables, such conclusion would be speculative.

D. How aggressively do institutions trade on cash-flow news?

The existence of the stock-price underreaction phenomenon implies that the price effects of some investors' underreaction are not "arbitraged away." In particular, the institutions are not buying enough stock in response to good cash-flow news to offset the selling by individuals.

The fact that institutional trading does not completely eliminate the underreaction phenomenon should not be a surprise, even if the institutions are not subject to any behavioral biases or exogenous constraints. In a market populated by other rational mean-variance optimizers, a mean-variance optimizer would follow the dictates of the CAPM and maximize diversification by holding each asset in proportion to its market capitalization. If these investors become aware that the market is underpricing certain stocks, they will recognize a benefit from shifting their wealth toward these assets.

However, a mean-variance optimizer will not keep buying the underpriced assets until those assets are no longer underpriced, because of the lost-diversification cost. In particular, if institutions bought a stock until it is only underpriced by a small amount, purchasing more of the stock would lead to a first-order loss in diversification with only a second-order gain in expected returns. Clearly, a mean-variance optimizing institution overweighs a stock subsequent to positive cash-flow news but not enough to completely offset the underweighing by individuals.

Do institutions as a group exploit the underreaction pattern as aggressively as a mean-variance optimizer would? We test whether the aggregate institutional portfolio is mean-variance efficient using the Black-Jensen-Scholes (1972) test. For simplicity, we use a single test asset: a managed portfolio that is long positive-cash-flow-news stocks and short negative-cash-flow-news stocks. The return on this test asset is regressed on aggregate institutional return less the risk-free rate. We find that the intercept of this regression is positive and thus reject the mean-variance efficiency of the institutional portfolio. Furthermore, the positive intercept indicates that the institutions as a group should trade more aggressively on news to reach the mean-variance optimum.

Table V shows the details of this test. We form our test-asset portfolio using the following procedure. On June 30 of year t, we estimate a VAR model from past data and compute the calendar year t-1 cash-flow news for each stock. The VAR includes log return, profitability, and book-to-market as state variables, and the data begin in 1954. Then, we set the portfolio weight for each stock equal to the year *t*-1 cash-flow news. Since the market-adjusted cash-flow-news terms have zero mean in each cross-section, the sum of the portfolio weights will be zero. (The sum of long weights is normalized to unity.) We compute monthly buy-and-hold returns for this cash-flow-news portfolio from July 1 to June 30 of the next year (*t*). This cash-flow-news portfolio return spans the period 7/81-12/98. The mean monthly return of this long-short portfolio is 0.65%, and the monthly return standard deviation is 3.51%. The monthly Sharpe ratio is 0.19, which is close to that of the market over the same period (0.19) and somewhat higher than that for the market over the 1926-99 period (0.13). We can reject the hypothesis that the mean return is zero with a t-statistic of 2.67. Regressed against the excess market return, this portfolio return has an alpha of 0.66% per month (t-statistic 2.67) and a beta of –0.01 (t-statistic –0.18). Consistent with other underreaction findings, the CAPM cannot price this portfolio return.

Next, we regress the return of the cash-flow-news portfolio on the excess return of aggregate institutional portfolio. The results are similar to those for the market: alpha of 0.65% with a 2.62 t-statistic; beta of 0.02 (t-statistic 0.13). We reject the hypothesis that the aggregate institutional portfolio is mean-variance efficient. Moreover, the positive sign on the intercept indicates that the inefficiency results from institutions exploiting the underreaction too little, rather than too much (see Treynor and Black [1973]).

Table V Panel C explores the actual portfolio allocations of institutions and individuals by regressing the institutional holdings on the CRSP value-weight portfolio and the cash-flow-news portfolio. These regressions indicate that the institutions have approximate 103% weight in the market and approximately 2% (t-statistic 3.21) weight in the cash-flow-news portfolio. In contrast, individuals appear to be 97% in the market and –2% (t-statistic –2.05) in the cash-flow-news portfolio. We find that the in-sample mean-variance optimal portfolio has approximately half the weight in each of the long-short portfolio and the aggregate institutional portfolio. Thus while the institutions are tilting their portfolio into right direction, this 2% weight is far from the in-sample optimum of weight equal to the market. This finding suggests that, given the prices, institutions are being far too conservative in exploiting the underreaction phenomenon.

In Table V, we also disaggregate institutional holdings into five groups: banks, insurance companies, mutual funds, investment advisors, and other institutions. Of these groups, banks appear to have performed the best during this sample period, delivering a mean return of 0.89% per month and a Sharpe ratio of 0.21. Our results suggest that none of the institutional-investor groups is mean-variance efficient, with Panel B alphas above 0.64% and t-statistics above 2.5. The portfolio allocations in the cash-flow-news portfolio range from 3.5% by banks to 1% by investment advisors. None of the disaggregate groups comes close to the in-sample optimum.

III. Additional robustness checks

A. Is bad news different from good news?

Hong, Lim, and Stein (2000) show that momentum profits are concentrated in the continuation of recent losers' returns. Hong, Lim, and Stein suggest that "*to the extent that stock prices do underreact, they are more prone to underreact to bad news than to good news*." To examine this possibility, we first compute the fitted values of cash-flow news using the VAR model of Table II. We then regress stock returns and institutional-ownership shock on a constant, cash-flow news, and the minimum of cash-flow news and zero. The results in Table VI confirm the conclusions of Hong, Lim, and Stein. For a typical stock, the average price reaction to one-dollar positive cash-flow news is 66 cents, while the average price reaction to one-dollar negative cash-flow news is 55 cents. In addition to the expected patterns in price responses, we also find that institutional ownership responds asymmetrically to cash-flow news. The regression coefficient of institutional-ownership shock on cash-flow news is 0.1038 for good news, but only 0.0724 for bad news.

We also estimate the asymmetric-response model for size quintiles. As in Table IV, we compute cash-flow news under two different assumptions. Panel B of Table VI assumes that all size quintiles share the same transition matrix Γ in estimation of the cash-flow-news terms. Panel C of Table VI uses cash-flow news estimated under the assumptions that stocks in different size quintiles have different transition matrices and that a stock's quintile assignment is permanent. Irrespective of the specific assumptions, the following patterns emerge. First, the asymmetry in price responses is much larger for small than for large stocks. This finding is consistent with that of Hong, Lim, and Stein (2000), who also argue that small stocks react especially sluggishly to bad news. Second, the institutional holdings respond more strongly to bad news for large stocks than for small stocks. For the largest stocks, institutional holdings actually respond with a higher coefficient to bad news than to good news.

These asymmetric-response results come with a caveat. Our methodology assumes that the predictive coefficients of the VAR state variables are symmetric, i.e., we do not allow for nonlinearities or kinks in the conditional expectation function. In practice this means that, for example, the predictive coefficient of returns on past returns is the same for negative and position past returns. Therefore, we interpret these results as a robustness check only. A more complete treatment of these asymmetries would require a more complicated nonlinear or piece-wise-linear time-series model.

B. Potential errors-in-variables problems

A potential concern with our underreaction measure is the attenuation bias arising from the errors-in-variables problem. Because we estimate the cash-flow-news terms, they are contaminated with sampling error. If this sampling error is independent of the true cash-flow news and returns, the regression coefficient of returns on estimated cash-flow news is biased towards zero.

To evaluate the magnitude of this bias, we estimate the bias in our underreaction-coefficient estimator using the jackknife. (Efron [1982] reviews jackknife bias estimation.) In summary, the attenuation bias turns out to be negligible. For example, the jackknife bias estimate for the underreaction coefficient in Panel C of Table III is –0.0035, which is economically insignificant relative to the point estimate of 0.5893. Other unreported simulation experiments also suggest that the bias is small. Our intuition is that the bias is negligible because the sampling error in the estimated cash-flow-news terms is not independent of the stock return. In effect, Campbell's (1991) VAR return-decomposition methodology gives the benefit of the doubt to cash-flow news: The VAR allocates the entire return to cash-flow news unless it finds evidence of the return reversing.

C. Potential selection biases and the influence of delisting events

Since we do not impose any restrictions on the dependent variables in the VAR estimation, our results are unlikely to be significantly influenced by selection biases. Under the assumptions that the population data are generated by the VAR and that the probability of a firm-year being included in the sample depends only on the lagged values of the state variables, the VAR parameters are estimated consistently if we do not impose any data requirements on the dependent variables of our regressions.

Of course, it is possible that the data-generating process changes when a firm is dropped from our sample. For example, a merger or delisting is likely to affect the VAR transition matrix. Since unobserved data are by definition not observable, we can only perform back-of-the-envelope robustness checks to control for this possibility. As such a robustness check, we take the estimated cash-flow-news terms from the VAR in Table II and regress returns and institutional-ownership shock on a constant, estimated cash-flow news, and a dummy variable. The dummy variable takes value one if the firm disappears from the sample during the year and zero otherwise. This regression and other similar experiments (e.g., including an interaction term) show that controlling for events that cause a firm to disappear from the sample does not change any of our stated results. Of course, this conclusion is conditional on the cash-flow-news terms being estimated correctly by the VAR model in Table II.

D. Expected simple returns and directly computed cash-flow news

The variation in expected log returns does not necessarily imply variation in expected simple returns. For example, if log returns are conditionally normal, the conditional expected simple return equals

$$E_{t-1}(1+R_t) = \exp\left[E_{t-1}(\log(1+R_t)) + \tfrac{1}{2}\operatorname{var}_{t-1}(\log(1+R_t))\right] . \tag{9}$$

Hence, expected log return may change simply because the conditional log-return variance changes. Another related concern is the size of the approximation error embedded into the cash-flow-news term in indirect computation of cash-flow news. To jointly examine these two issues, we estimate a VAR specification with simple instead of log returns and add the clean-surplus ROE to the state vector. This VAR enables us to examine the response of expected simple returns to directly computed cash-flow news. Figure 5 shows the responses of expected simple returns and institutional ownership to directly computed cash-flow news and illustrates that our results are not artifacts of either Jensen's inequality or the approximation error.

E. Alternative VAR specifications

We also confirm our basic results by estimating a richer VAR specification. The predictive variables include three lags of past stock returns, two lags of profitability, two lags of institutional ownership, and one lag of the book-to-market ratio and leverage. The qualitative results obtained from this more elaborate specification are similar to the main results obtained from our simple VAR. The regression coefficients of return and institutional-ownership shock on cash-flow news are approximately 0.5 and 0.05. Due to the additional free parameters, the standard errors of these estimates are somewhat larger at 0.1 and 0.01. Generally, our qualitative results are not sensitive to the lag order, and many other elaborate specifications give similar results.

IV. Conclusions

Prior research has documented the tendency of stock prices to underreact to news about cash flows. To further investigate this underreaction phenomenon, we analyze the dynamics of returns, cash-flow news, and trading between individual and institutional investors using a vector autoregression and data on individual stocks. We assume that trading among investors does not cause firms' expected cash flows and, therefore, treat cash-flow news as exogenous.

Our main finding is that in response to positive cash-flow news, institutions in the aggregate buy shares from individuals, thus exploiting the underreaction phenomenon. The effect is economically significant: Institutions, which hold on average 36% of a typical stock, buy an additional 4% of the outstanding shares in response to a one-standard-deviation shock to expected future cash flows. The institutions are not simply following price-momentum strategies (or following mechanical market-capitalization rules and thereby buying larger stocks and selling smaller): When a stock's price increases 25% without any concomitant cash-flow news, institutions sell 5% of the outstanding shares to individuals. Our main results are robust to a number of methodological variations.

We offer two different interpretations of our results. On the one hand, if one assumes that the underreaction pattern in prices is due to investor irrationality, individuals appear to be the main culprits. They buy stocks during price run-ups that are unrelated to cash-flow fundamentals and do not appear to adjust their demand curves for shares sufficiently in response to new cash-flow information. On the other hand, one may assume rational expectations and that the positive cash-flow news is followed by high expected returns because positive cash-flow news coincides with an increase in risk. Since this increase in risk induces selling by individuals to institutions, this (yet unidentified) risk must be of especially significant concern to individual investors.

If the underreaction phenomenon is due to investor irrationality, why does the institutional trading not eliminate the underreaction? Since the strategy the institutions are following requires sacrificing diversification by overweighing the stocks with recent positive cash-flow news, it would not be in the interest of institutions to buy until the stocks are no longer mispriced. Rather, there is an optimal amount of buying that will lead to an efficient portfolio. We test the efficiency of the aggregate institutional portfolio and find that it is not mean-variance efficient. The institutions as a group are less aggressive in buying positive-cash-flow-news stocks and selling negative-cash-flow-news stocks than a rational mean-variance optimizer would be.

The trading patterns between individuals and institutions may also cast light on the cross-sectional underreaction patterns. The institutional response to cash-flow news is weakest among small stocks; small stocks also show the strongest underreaction patterns. This finding is consistent with institutions facing exogenous constraints in trading small stocks. We speculate that agency considerations may play a role in constraining the institutional investment outside the universe of large-capitalization stocks.

Our results are inconsistent with the hypothesis that institutional investors follow positive-feedback investment strategies (Lakonishok, Shleifer, and Vishny [1992] and others). According to our results, institutional investors follow cash-flow-momentum strategies, but are contrarian relative to price moves that are unrelated to cash flows. If cash-flow news is exogenous, such institutional buying cannot feed back to cause more institutional buying. Also, because the institutions do not appear to "jump in" during "price rallies" that are not justified by cash-flow fundamentals, it is difficult to classify institutions as either the noise traders or the sophisticated investors in the destabilizing-speculation model of DeLong, Shleifer, Summers, and Waldmann (1990). At minimum, our results suggest that future empirical studies investigating investors' trading behavior or testing herding or positive-feedback-trading theories should carefully separate the effects of earnings momentum and price momentum.

The investment patterns of individuals and institutions may also shed some light on one of the major trends in the U.S. capital markets. The percentage of domestic equities held by institutions has risen from 16% in 1965 to above 50% in 1998 (Pirinsky [2000]). It is possible that this trend is part of an institutional response to the deficiencies of individuals as direct investors. Of course, while institutions may have better stock selection ability than individuals, it is not necessarily the case that institutions consistently deliver higher net returns to the investors. Our data do not include expenses, which are likely to be of the order of the institutions' performance edge.

Appendix 1: Approximate present-value model

Three main assumptions are made to derive the ROE-based version of the approximate present-value model of Vuolteenaho (2001a). First, book equity (B), dividend (D), and market equity (M) are assumed to be strictly positive. Second, the difference between log book equity (b) and log market equity (m) and the difference between log dividend (d) and log book equity are assumed to be stationary, even though the series individually have an integrated component. Third, earnings (X), dividends, and book equity must satisfy the clean-surplus identity:

$$B_t = B_{t-1} + X_t - D_t \tag{A1.1}$$

– book equity this year equals book equity last year plus earnings less dividends.

Market and accounting returns (i.e., ROE) can be expressed as

$$r_t \equiv \log\left(\frac{M_t + D_t}{M_{t-1}}\right) = \log\left(1 + \frac{\Delta M_t + D_t}{M_{t-1}}\right) = \log(1 + R_t) \tag{A1.2}$$

$$e_t \equiv \log\left(\frac{B_t + D_t}{B_{t-1}}\right) = \log\left(1 + \frac{\Delta B_t + D_t}{B_{t-1}}\right) = \log(1 + E_t) \tag{A1.3}$$

where ROE is denoted by $e_t = \log(1 + X_t / B_{t-1})$, the log stock return by $r_t = \log(1 + R_t)$, and the simple stock return by R_t.

Substituting the log dividend-growth rate, Δd_t, the log dividend-price ratio, δ_t, and the log dividend-to-book-equity ratio, $\gamma_t \equiv d_t - b_t$, to the return definitions (A1.2) and (A1.3):

$$r_t = \log(\exp(-\delta_t) + 1) + \Delta d_t + \delta_{t-1}. \tag{A1.4}$$

$$e_t = \log(\exp(-\gamma_t) + 1) + \Delta d_t + \gamma_{t-1}. \tag{A1.5}$$

The nonlinear functions (A1.4) and (A1.5) can be approximated around $\hat{\delta}$ and $\hat{\gamma}$. Specifically, use some convex combination of the unconditional means of the variables as an expansion point for both functions. Subtracting r_t from e_t, the approximate expression is

$$e_t - r_t = \log(\exp(-\gamma_t) + 1) - \log(\exp(-\delta_t) + 1) + (\gamma_{t-1} - \delta_{t-1}) \approx \rho\theta_t - \theta_{t-1}. \tag{A1.6}$$

Above, the log book-to-market ratio is denoted by θ_t. Note that as dividend yields drop, the approximation becomes more accurate, while ρ approaches unity.

Next, the one period approximation is iterated forward to yield:

$$\theta_{t-1} = \sum_{j=0}^{N} \rho^j r_{t+j} - \sum_{j=0}^{N} \rho^j e_{t+j} + \sum_{j=0}^{N} \rho^j \xi_{t+j} + \rho^{N+1}\theta_{t+N} \tag{A1.7}$$

ξ_t denotes the approximation error in equation (A1.7). Because $\rho < 1$, the limit $N \to \infty$ of equation (A1.7) converges to

$$\theta_{t-1} = k_{t-1} + \sum_{j=0}^{\infty} \rho^j r_{t+j} - \sum_{j=0}^{\infty} \rho^j e_{t+j} \tag{A1.8}$$

The approximation error of equation (A1.8) is defined as $k_{t-1} \equiv \sum_{j=0}^{\infty} \xi_{t+j}$.

Equation (A1.8) allows one to decompose the unexpected stock return into an expected-return component and a cash-flow component, along the lines of Campbell (1991). We take the change in expectations of (A1.8) from $t-1$ to t and reorganize:

$$r_t - E_{t-1} r_t = \Delta E_t \sum_{j=0}^{\infty} \rho^j e_{t+j} - \Delta E_t \sum_{j=1}^{\infty} \rho^j r_{t+j} + \kappa_t \,, \tag{A1.9}$$

where ΔE_t denotes the change in expectations from $t-1$ to t (i.e., $E_t(\cdot) - E_{t-1}(\cdot)$).

Which value to pick for ρ is an empirical question. We follow Vuolteenaho (2001b) and use an OLS regression to pick the discount coefficient. (We regress beginning-of-the-period log book-to-market plus log profitability minus log return on end-of-the-period log book book-to-market.) In our data, a 99.82% R^2 is achieved with $\rho = .97$. Because ρ is estimated accurately and our main results are not sensitive to the ρ-choice, we use this ρ-value in the analysis and treat it as a constant. Further experiments performed by Vuolteenaho (2001b) show that the multi-period approximation is very accurate in a sample similar to ours. Furthermore, the results of this paper are insensitive to small changes in the discount coefficient: All of the main empirical results can be reproduced with ρ set to 0.95 or 1.00.

Appendix 2: Data

A. CRSP-COMPUSTAT data

The basic data come from the CRSP-COMPUSTAT intersection. The Center for Research in Securities Prices (CRSP) monthly stock file contains monthly prices, shares outstanding, dividends and returns for NYSE, AMEX, and NASDAQ stocks. The COMPUSTAT annual research file contains the relevant accounting information for most publicly traded US stocks.

In order to be included in our sample, a firm-year must satisfy the following COMPUSTAT data requirements. First, we require all firms to have a December fiscal-year end of *t*-1, in order to align accounting variables across firms. Second, a firm must have *t*-1, *t*-2, and *t*-3 book equity available, where *t* denotes time in years. A number of CRSP data requirements must also be satisfied. A valid market-equity figure must be available for *t*-1, *t*-2, and *t*-3. We require that there is a valid trade during the month immediately preceding the period *t* return. This requirement ensures that the return predictability is not spuriously induced by stale prices or other similar market micro-structure issues. We also require at least one monthly return observation during each of the preceding five years, from *t*-1 to *t*-5. In addition, we screen out clear data errors and mismatches by excluding firms with *t*-1 market equity less than $10 million and book-to-market more than 100 or less than 1/100. We carefully avoid imposing any COMPUSTAT or CRSP requirements on year *t* data, because these data are used in the dependent variables of our regressions.

The stock returns are calculated as follows. The simple stock return is an annual value-weight return on a firm's common stock issues (typically one). If no return data are available, we substitute zeros for both returns and dividends. Annual returns are compounded from monthly returns, recorded from the beginning of July to the end of June. Delisting returns are included when available in CRSP. If a firm is delisted but the delisting return is missing, we investigate the reason for disappearance. If the delisting is performance-related, we assume a –30% delisting return. Otherwise, we assume a zero delisting return.[4]

Market equity (combined value of all common stock classes outstanding) is taken from CRSP as of the end of June. If the year *t* market equity is missing, we compound the lagged market equity with return without dividends.

For book equity, we prefer COMPUSTAT data item 60, but if it is unavailable we use item 235. Also, if short- and/or long-term deferred taxes are available (data items 35 and 71), we add them to book equity. If both data items 60 and 235 are unavailable, we proxy book equity by the last period's book equity plus earnings less dividends. If neither earnings nor book equity is available, we assume that the book-to-market ratio has not changed and compute the book equity proxy from the last period's book-to-market and this periods market equity. We treat negative or zero book equity values as missing.

GAAP ROE is the earnings over the last period's book equity, measured according to the U.S. Generally Accepted Accounting Principles. We use the COMPUSTAT data item 172, earnings available for common. When earnings are missing, earnings is computed as the change in book equity plus dividends. In every case, we do not allow the firm to lose more than its book equity. That is, we define the net income as maximum of reported net income (or clean-surplus net income, if earnings are not reported) and negative of the beginning of the period book equity. Hence, the minimum GAAP ROE is truncated to –100%.

We calculate leverage as book equity over the sum of book equity and book debt. The book debt is the sum of debt in current liabilities (34), total long-term debt (9), and preferred stock (130).

The identities necessitate the use of log transforms of stock return, profitability and the book-to-market ratio. The log transformations may cause problems if some stock returns and/or ROEs are close to –100% or if some of the book-to-market ratios are close to zero or infinity. We follow Vuolteenaho (2001b) and solve this complication by redefining the firm as a portfolio of 90% common stock and 10% Treasury-bills using market values. Every period, the portfolio is rebalanced to these weights. This affects not only stock return and accounting return on equity, but also the book-to-market equity, pulling this ratio slightly towards one. After adding this risk-free investment, the ratios and returns are sufficiently well behaved for log transformations. Simple market and accounting returns on this portfolio closely approximate simple returns on the firm's common stock only. The accounting identities hold for the transformed quantities. Furthermore, this transformation method is superior to purely statistical transformations (such as the Box-Cox transformation), because the transformed quantities still correspond to an investment strategy. The results are robust to moderate perturbations (+/- 0.025) of the T-bill weight.

B. SPECTRUM data

A 1978 amendment to the Securities and Exchange Act of 1934 required all institutions with greater than $100 million of securities under discretionary management to report their holdings to the SEC. Holdings are reported quarterly on the SEC's form 13F; all common-stock positions greater than 10,000 shares or $200,000 must be disclosed. These reports are available in electronic form back to 1980 from CDA/Spectrum, a firm hired by the SEC to process the 13F filings. Our data include the quarterly reports from the first quarter of 1980 through the fourth quarter of 1999. Throughout this paper, we use "institution", "large institution", and "manager" as synonyms for "an institution that files a 13F".

On the 13F, each manager must report all securities over which they exercise sole or shared investment discretion. In cases where investment discretion is shared by more than one institution, care is taken to prevent double counting. Spectrum officials have told us that they believe that duplication is rare. Once an institution enters the 13F sample, it is assigned a manager type by Spectrum. The five types are (1) bank, (2) insurance company, (3) investment company (mutual fund), (4) investment advisor, and (5) other. The first three categories are self-explanatory; the investment advisor category includes most of the large brokerage firms; the "other" category includes pension funds and university endowments. These categorizations are not always precise; for example, brokerage firms with mutual fund subsidiaries will fall into category (3) if the mutual funds are deemed by Spectrum to make up more than 50 percent of the total 13F assets for that manager and into category (4) otherwise. Spectrum does not provide information to allow more precise partitioning of the data. It is also possible for a manager to be reclassified over time if Spectrum determines that the institution's main business has changed.

The Spectrum 13F holdings file contains three columns: date, CUSIP, identifier for the institution, and number of shares held in that stock by that institution on that date. All dates are end-of-quarter (3/31, 6/30, 9/30, or 12/31). For each CUSIP and date we simply sum up the shares held by all institutions in the sample to get total institutional holdings of the security at the end of that quarter. We then match each CUSIP to a CRSP PERMNO, the permanent number CRSP assigns to that security. Holdings associated with CUSIPs for which we found no associated PERMNO are ignored; these account for a very small fraction of institutional holdings (future drafts will include additional CUSIPs which we are currently hand-matching to PERMNOs). Some companies have multiple equity securities associated with them; CRSP uniquely identifies each firm with a permanent company number, or PERMCO. We value-weight returns and institutional holding percentages of the different share classes (PERMNOs) associated with each PERMCO. This gives us one return and one institutional ownership percentage associated with each set of accounting data.

Our primary results are based on annual vector autoregressions. In these VARs we use end-of-year t-1 accounting information to predict returns from July of year t through June of year t+1. We use institutional ownership data as of June 30 of year t as the variable corresponding to the returns over this period. However, the results are robust to using the March 31 or December 31 (of the previous year) institutional ownership instead.

In some of our tests we use monthly data. For this purpose we compute the percentage of institutional ownership at the end of each quarter and assume that the number stays constant over the subseqent three months. In this way, we can compute monthly returns on the aggregate institututional portfolio. We define all outstanding shares not held by 13F institutions to be "individual" or "household" holdings. (Our "individual" holdings thus contain assets controlled by very small financial intitutions, but these make up only a tiny percentage of the category.) Therefore, for each stock the individual holding fraction is simply one minus the institutional ownership.

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Table I: Descriptive statistics

Panel A reports means, standard deviations, and percentiles (minimum, 25%, 50%, 75%, and maximum) of log return, r; log US GAAP return on equity, e^{GAAP}; log book-to-market, θ; the fraction of institutional ownership, *if*; and the change in institutional-ownership fraction, *dif*. Panel B reports the contemporaneous correlations and Panel C the first-order cross- and autocorrelations of the variables. Appendix B contains the details of data sources and variable definitions. The data consists of 23,501 firm-years and spans period 1983-1998 (16 years). The descriptive statistics are estimated from pooled data.

Panel A: Basic descriptive statistics

Variable	Mean	St. Dev.	Min	25%-pct	Median	75%-pct	Max
r	0.074	0.343	-2.185	-0.093	0.094	0.268	2.757
e^{GAAP}	0.027	0.353	-2.526	0.036	0.095	0.143	3.919
θ	-0.389	0.608	-4.449	-0.754	-0.351	0.008	3.557
if	0.363	0.226	0.000	0.172	0.351	0.540	0.986
dif	0.005	0.106	-0.957	-0.022	0.008	0.045	0.930

Panel B: Contemporaneous correlations

Variable	r	e^{GAAP}	θ	*if*	*dif*
r	1	0.326	-0.372	0.151	0.175
e^{GAAP}	0.326	1	0.113	0.197	0.086
θ	-0.372	0.113	1	-0.136	-0.06
if	0.151	0.197	-0.136	1	0.297
dif	0.175	0.086	-0.060	0.297	1

Panel C: First-order cross- and autocorrelations

Variable	$r(t)$	$e^{GAAP}(t)$	$\theta(t)$	$if(t)$	$dif(t)$
$r(t-1)$	0.142	0.318	-0.216	0.142	0.048
$e^{GAAP}(t-1)$	0.136	0.534	0.082	0.168	0.02
$\theta(t-1)$	0.041	-0.06	0.771	-0.13	-0.013
$if(t-1)$	0.071	0.161	-0.111	0.885	-0.181
$dif(t-1)$	0.016	0.084	-0.051	0.141	-0.159

Table II: VAR parameter estimates

The table reports the VAR parameter estimates. The model state variables include the market-adjusted log stock return, $\tilde{r}$, (the first element of the state vector z); market-adjusted log book-to-market ratio, $\tilde{\theta}$, (the second element); market-adjusted log profitability, $\tilde{e}$, (the third element); and market-adjusted fraction of shares outstanding owned by institutions, $\widetilde{if}$, (the fourth element). The parameters in the table correspond to the following system:

$$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t}, \quad \Sigma = E(u_{i,t}u'_{i,t})$$

We report three numbers for each parameter. The first number (bold) is a weighted least squares estimate of the parameter, where observations are weighted such that each cross-section receives an equal weight. The second number (in parentheses) is a robust standard error computed using Rogers's (1983, 1993) method (details of the method are described by Vuolteenaho [2001b]). The third number (in brackets) is a robust jackknife standard error computed using the jackknife method of Shao and Rao (1993).

Coefficient estimates for the first order market-adjusted VAR — **(estimate),** (s.e.), [j.s.e.]

	Γ				**Σ**			
$\tilde{r}_t$	**0.1694**	**0.0609**	**0.0986**	**0.0759**	**0.1009**	**-0.0782**	**0.0258**	**0.0058**
	(0.0334)	(0.0169)	(0.0210)	(0.0161)	(0.0063)	(0.0056)	(0.0019)	(0.0009)
	[0.0349]	[0.0176]	[0.0218]	[0.0166]	[0.0065]	[0.0058]	[0.0019]	[0.0009]
$\tilde{\theta}_t$	**0.1593**	**0.8229**	**0.0970**	**-0.0689**	**-0.0782**	**0.1330**	**0.0246**	**-0.0033**
	(0.0256)	(0.0215)	(0.0266)	(0.0175)	(0.0056)	(0.0069)	(0.0027)	(0.0009)
	[0.0267]	[0.0224]	[0.0279]	[0.0181]	[0.0058]	[0.0071]	[0.0028]	[0.0009]
$\tilde{e}_t$	**0.2336**	**0.0012**	**0.6048**	**0.0921**	**0.0258**	**0.0246**	**0.0810**	**0.0028**
	(0.0201)	(0.0079)	(0.0207)	(0.0125)	(0.0019)	(0.0027)	(0.0054)	(0.0003)
	[0.0210]	[0.0081]	[0.0214]	[0.0129]	[0.0019]	[0.0028]	[0.0055]	[0.0003]
$\widetilde{if}_t$	**0.0185**	**-0.0035**	**0.0147**	**0.9062**	**0.0058**	**-0.0033**	**0.0028**	**0.0101**
	(0.0047)	(0.0027)	(0.0044)	(0.0081)	(0.0009)	(0.0009)	(0.0003)	(0.0009)
	[0.0049]	[0.0028]	[0.0046]	[0.0084]	[0.0009]	[0.0009]	[0.0003]	[0.0010]

Table III: Responses of price and institutional ownership to cash-flow news

The table reports derived statistics calculated from the VAR specification of Table II. The VAR specification has the structure

$$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t}, \quad \Sigma = E(u_{i,t}u'_{i,t})$$

The model variables include the market-adjusted log stock return, market-adjusted log book-to-market ratio, market-adjusted log profitability, and market-adjusted institutional-ownership fraction.

Panel A reports the covariance and correlation matrices of expected-return news, cash-flow news, and institutional-ownership shock. The upper-left section (including diagonal) of the panel shows covariances and the shaded lower-left section correlations. Panel B reports the covariance and correlation matrices of one-period expected return, long-horizon expected return, and the fraction of institutional ownership. The long-horizon expected-return measure is defined as $\tilde{p}_{r,t-1} \equiv \sum_{j=0}^{\infty} \rho^j E_{t-1}\tilde{r}_{t+j}$. The upper-left section (including diagonal) of the panel shows covariances and the shaded lower-left section correlations. Panel C shows the simple regression coefficients of return and institutional-ownership shock on cash-flow news.

The first number (bold) is a point estimate computed using the weighted least squares estimates of the parameters. The second number (in brackets) is a robust jackknife standard error computed using the jackknife method of Shao and Rao (1993).

Panel A: Covariances and correlations (shaded) of news and insitutional-ownership shock

	Expected-return News (Nr)	Cash-flow news (Ncf)	Institutional-ownership shock
Expected-return News (Nr)	**0.0619** [0.0208]	**0.0896** [0.0274]	**0.0122** [0.0027]
Cash-flow News (Ncf)	**0.7713** [0.0598]	**0.2182** [0.0379]	**0.0180** [0.0029]
Institutional-Ownership shock	**0.4871** [0.0797]	**0.3823** [0.0371]	**0.0101** [0.0010]

Panel B: Covariances and correlations (shaded) of expected returns and insitutional ownership

	One-period expected return	Long-horizon expected return	Institutional ownership
One-period expected return	**0.0088** [0.0027]	**0.0428** [0.0142]	**0.0100** [0.0025]
Long-horizon expected return	**0.9076** [0.0349]	**0.2524** [0.0885]	**0.0821** [0.0216]
Institutional ownership	**0.4147** [0.0646]	**0.6395** [0.0949]	**0.0653** [0.0069]

Panel C: Simple regression coefficients

Stock return on cash-flow news	**0.5893** [0.0616]
Institutional-ownership shock on cash-flow news	**0.0823** [0.0092]

Table IV: Results for size groups

The table reports the results for different size groups. Panel A assumes that all size quintiles share the same transition matrix Γ but may have different error covariance matrices Σ. Panel B assumes that stocks in different size quintiles have different transition matrices and error covariance matrices. In Panel B, the quintile assignment is assumed to be permanent.

The VAR specification has the structure

$$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t}, \quad \Sigma(\text{characteristics}) = E(u_{i,t}u'_{i,t} \mid \text{characteristics})$$

The model variables include the market-adjusted log stock return, $\tilde{r}$, (the first element of the state vector z); market-adjusted log book-to-market ratio, $\tilde{\theta}$, (the second element); market-adjusted log profitability, $\tilde{e}$, (the third element); and market-adjusted fraction of shares outstanding owned by institutions, $\widetilde{if}$, (the fourth element). The characteristic affecting the error covariance matrix is size-group assignment.

For every size group, we report four statistics: the variance of expected-return news (var(Nr)), the variance of cash-flow news (var(Ncf)), the simple regression coefficient of return on cash-flow news (b(r,Ncf)), and the simple regression coefficient of institutional-ownership shock on cash-flow news (b(if,Ncf)).

For each statistic, we report two numbers. The first number (bold) is a point estimate computed using the weighted least squares estimates of the parameters. The second number (in brackets) is a robust jackknife standard error computed using the jackknife method of Shao and Rao (1993).

Panel A: Size quintiles, common transition matrix

Quintile	Var(Nr)	Var(Ncf)	b (r,Ncf)	b (if,Ncf)
Small	**0.1273** [0.0434]	**0.4234** [0.0711]	**0.5585** [0.0681]	**0.0455** [0.0058]
2	**0.0738** [0.0225]	**0.2708** [0.0417]	**0.5965** [0.0611]	**0.0800** [0.0074]
3	**0.0572** [0.0174]	**0.2062** [0.0347]	**0.5937** [0.0552]	**0.1038** [0.0147]
4	**0.0326** [0.0104]	**0.1177** [0.0225]	**0.6255** [0.0610]	**0.1479** [0.0183]
Big	**0.0187** [0.0061]	**0.0738** [0.0136]	**0.6686** [0.0643]	**0.1375** [0.0155]
Small-Big	**0.1086** [0.0382]	**0.3496** [0.0599]	**-0.1100** [0.0375]	**-0.0920** [0.0139]

Panel B: Size quintiles, permanent group assignment

Quintile	Var(Nr)	Var(Ncf)	b (r,Ncf)	b (if,Ncf)
Small	**0.1301** [0.0594]	**0.4202** [0.0850]	**0.5545** [0.0875]	**0.0301** [0.0069]
2	**0.0757** [0.0377]	**0.2517** [0.0626]	**0.5994** [0.0987]	**0.0680** [0.0106]
3	**0.0284** [0.0170]	**0.1470** [0.0325]	**0.7289** [0.0926]	**0.0634** [0.0255]
4	**0.0115** [0.0070]	**0.0640** [0.0111]	**0.8931** [0.1069]	**0.0714** [0.0291]
Big	**0.0013** [0.0018]	**0.0403** [0.0094]	**1.0090** [0.0913]	**0.0768** [0.0442]
Small-Big	**0.1288** [0.0596]	**0.3799** [0.0828]	**-0.4544** [0.1255]	**-0.0467** [0.0441]

Table V: Tests of mean-variance efficiency

The table tests the mean-variance efficiency of aggregate institutional holdings, aggregate individual holdings, holdings of disaggregate groups of institutions, and the CRSP value-weight portfolio. Panel A shows descriptive statistics. Panel B shows the Black-Jensen-Scholes (1972) test of mean-variance efficiency of a given portfolio. As the test asset, we use a portfolio that goes long in stocks that have experienced positive cash-flow news in the past and goes short in stocks that have experienced negative cash-flow news in the past (labeled "Ncf portfolio"). In this portfolio, the stocks have weights proportional to their past cash-flow news. The cash-flow-news series are estimated using past data only, using a first-order VAR with market-adjusted log return, ROE, and book-to-market in the state vector. The VAR data are the 1954-1998 CRSP-COMPUSTAT intersection used by Vuolteenaho (2001b). Panel C regresses the portfolio returns on the returns of the CRSP value-weight portfolio and the zero-investment cash-flow-news portfolio. Appendix 2 contains descriptions of disaggregate groups of institutions.

Panel A: Descriptive statistics, monthly returns 7/1981-12/1998.

Portfolio return	Mean	Standard dev.	Sharpe ratio
CRSP VW – RF	0.81%	4.37%	0.1857
Ncf portfolio	0.65%	3.51%	0.1853
Institutions – RF	0.87%	4.54%	0.1908
Individuals – RF	0.75%	4.25%	0.1775
Banks – RF	0.89%	4.34%	0.2063
Insurance companies – RF	0.87%	4.52%	0.1926
Mutual funds– RF	0.87%	4.71%	0.1849
Investment advisors – RF	0.85%	4.72%	0.1809
Other institutions – RF	0.84%	4.41%	0.1896

Panel B: Time-series regressions to test efficiency, monthly returns 7/1981-12/1998.

Portfolio return	Alpha (t-stat)	Beta (t-stat)	Dependent variable	R^2
Ncf portfolio	0.66% (2.67)	-0.010 (-0.18)	CRSP VW – RF	0.00
Ncf portfolio	0.65% (2.62)	0.002 (0.03)	Institutions – RF	0.00
Ncf portfolio	0.67% (2.71)	-0.024 (-0.42)	Individuals – RF	0.00
Ncf portfolio	0.64% (2.58)	0.013 (0.22)	Banks – RF	0.00
Ncf portfolio	0.65% (2.63)	-0.001 (-0.01)	Insurance companies – RF	0.00
Ncf portfolio	0.65% (2.64)	-0.001 (-0.03)	Mutual funds– RF	0.00
Ncf portfolio	0.65% (2.65)	-0.004 (-0.07)	Investment advisors – RF	0.00
Ncf portfolio	0.65% (2.62)	0.004 (0.07)	Other institutions – RF	0.00

Panel C: Time-series regressions to measure portfolio weights, monthly returns 7/1981-6/1998.

Portfolio return	Alpha (t-stat)	Weight on CRSP VW (t-stat)	Weight on the Ncf portfolio (t-stat)	R^2
Institutions – RF	0.01% (0.58)	1.0375 (216)	0.0191 (3.21)	0.996
Individuals – RF	-0.02% (-0.46)	0.9655 (122)	-0.0202 (-2.05)	0.986
Banks – RF	0.07% (2.54)	0.9882 (162)	0.0345 (4.53)	0.992
Insurance companies – RF	0.02% (0.99)	1.0305 (197)	0.0151 (2.32)	0.995
Mutual funds– RF	-0.01% (-0.23)	1.0724 (133)	0.0142 (1.42)	0.988
Investment advisors – RF	-0.02% (-0.74)	1.0758 (147)	0.0097 (1.06)	0.990
Other institutions – RF	0.00% (0.22)	1.0034 (135)	0.0221 (2.39)	0.989

Table VI: Asymmetric response to good and bad news

The table documents the asymmetric response of returns and institutional ownership to good and bad cash-flow news. First, we use the VAR model of Table II to compute the fitted values of the news terms. Second, we regress the market-adjusted stock return and estimated market-adjusted ownership shock on a constant, cash-flow news, and the minimum of zero and cash-flow news:

$$\begin{bmatrix} \tilde{r}_t \\ u_t(\tilde{if}) \end{bmatrix} = \begin{bmatrix} a_2 \\ a_2 \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \tilde{N}_{cf,t} \\ \tilde{N}_{cf,t}neg \end{bmatrix} + \begin{bmatrix} e_{1,t} \\ e_{2,t} \end{bmatrix}$$

$u(\tilde{if})$ is the estimated institutional-ownership shock from the VAR of Table II, $\tilde{r}$ market-adjusted stock return, $\tilde{N}_{cf}$ estimated cash-flow news, and $\tilde{N}_{cf}neg$ minimum of zero and estimated cash-flow news.

Panel A shows the regression coefficients estimated from the entire sample. Panels B and C show the regression coefficients for different size groups. Panel B assumes that all size quintiles share the same transition matrix Γ in estimation of the cash-flow-news terms. Panel C uses cash-flow news estimated under the assumptions that stocks in different size quintiles have different transition matrices and that a stock's quintile assignment is permanent.

For each statistic, we report two numbers. The first number (bold) is a point estimate computed using the pooled-OLS estimates of the parameters. The second number (in brackets) is a robust jackknife standard error computed using the jackknife method of Shao and Rao (1993).

Panel A: Asymmetric response to news for all firms

	b_{11} (r,Ncf)	b_{12} (r,Ncf neg)	b_{21} (if,Ncf)	b_{22} (if,Ncf neg)
All firms	**0.6582** [0.0713]	**-0.1076** [0.0424]	**0.1038** [0.0108]	**-0.0314** [0.0084]

Panel B: Size quintiles, common transition matrix

Quintile	b_{11} (r,Ncf)	b_{12} (r,Ncf neg)	b_{21} (if,Ncf)	b_{22} (if,Ncf neg)
Small	**0.6837** [0.0971]	**-0.1782** [0.0825]	**0.0612** [0.0111]	**-0.0254** [0.0098]
2	**0.6646** [0.0833]	**-0.1116** [0.0650]	**0.1154** [0.0139]	**-0.0568** [0.0160]
3	**0.6671** [0.0643]	**-0.1170** [0.0481]	**0.1388** [0.0142]	**-0.0507** [0.0154]
4	**0.6347** [0.0549]	**-0.0442** [0.0628]	**0.1441** [0.0156]	**0.0138** [0.0315]
Big	**0.6756** [0.1035]	**-0.0666** [0.1828]	**0.1050** [0.0082]	**0.0715** [0.0437]
Small-Big	**0.0081** [0.1235]	**-0.1115** [0.2429]	**-0.0438** [0.0135]	**-0.0969** [0.0489]

Panel C: Size quintiles, permanent group assignment

Quintile	b_{11} (r,Ncf)	b_{12} (r,Ncf neg)	b_{21} (if,Ncf)	b_{22} (if,Ncf neg)
Small	**0.6833** [0.1133]	**-0.1972** [0.0906]	**0.0303** [0.0180]	**0.0005** [0.0182]
2	**0.7049** [0.1252]	**-0.1699** [0.0725]	**0.0995** [0.0240]	**-0.0500** [0.0237]
3	**0.8487** [0.0920]	**-0.1788** [0.0654]	**0.0407** [0.0557]	**0.0379** [0.0544]
4	**0.9419** [0.0884]	**-0.0869** [0.0931]	**0.0308** [0.0570]	**0.0761** [0.0645]
Big	**1.0170** [0.1052]	**-0.0131** [0.2125]	**0.0281** [0.0661]	**0.0993** [0.0482]
Small-Big	**-0.3337** [0.1636]	**-0.1840** [0.2794]	**0.0022** [0.0674]	**-0.0987** [0.0532]

Figure 1. Time-series evolution of variables.

The figure graphs the time series of cross-sectional percentiles (5%, 25%, 50%, 75%, 95%) for the following variables: log return, r; log return on equity, e^{GAAP}; fraction of institutional ownership, if; and log book-to-market, θ. For a more detailed definition of the variables and data, see Appendix B.

Figure 2. Price response to shocks.

The figure contains two impulse-response functions computed from the VAR system of Table II. The first graph shows the cumulative response of market-adjusted log returns to typical 25% cash-flow news. The typical 25% cash-flow news is induced by setting the VAR-error vector to a constrained maximum likelihood value, imposing the constraint that cash-flow news equals 0.25.

The second graph shows the cumulative response of market-adjusted log returns to a 25% unexpected return in the absence of cash-flow news. The 25% return shock is induced by setting the first element of the VAR-error vector to 0.25. The other elements of the VAR-error vector are set to their conditional expectations, conditional on the first element being equal to 0.25 and cash-flow news equal to zero.

Dashed lines denote +/- 2 standard-error bounds, calculated using the jackknife.

Figure 3. Response of institutional ownership to shocks.

The figure contains two impulse-response functions computed from the VAR system of Table II. The first graph shows the response of institutional ownership to typical 25% cash-flow news. The typical 25% cash-flow news is induced by setting the VAR-error vector to a constrained maximum likelihood value, imposing the constraint that cash-flow news equals 0.25.

The second graph shows the response of institutional ownership to a 25% unexpected return in the absence of cash-flow news. The 25% return shock is induced by setting the first element of the VAR-error vector to 0.25. The other elements of the VAR-error vector are set to their conditional expectations, conditional on the first element being equal to 0.25 and cash-flow news equal to zero.

Dashed lines denote +/- 2 standard-error bounds, calculated using the jackknife.

Figure 4. Results for size groups.

The top two figures graph the results for different size quintiles from Table IV Panel A. The upper-left figure plots the regression coefficient of return on cash-flow news, and the upper-right figure plots the regression coefficient of institutional-ownership shock on cash-flow news.

The bottom two figures graph the results for different size quintiles from Table IV Panel B. The lower-left figure plots the regression coefficient of return on cash-flow news, and the lower-right figure plots the regression coefficient of institutional-ownership shock on cash-flow news.

Dashed lines denote +/- 2 standard-error bounds, calculated using the jackknife.

Figure 5. Impulse responses using simple returns and directly computed cash-flow news.

The figure contains two impulse-response functions to directly computed cash-flow news. The VAR specification has the structure:

$$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t}, \quad \Sigma = E(u_{i,t}u'_{i,t})$$

The VAR state vector includes the market-adjusted simple stock return, market-adjusted log book-to-market ratio, market-adjusted log GAAP profitability, market-adjusted log clean-surplus profitability, and market-adjusted fraction of institutional ownership. Define $e4' \equiv [0 \quad \cdots \quad 0 \quad 1]$. Direct cash-flow news can be conveniently expressed as $e4'(I - \rho\Gamma)^{-1}u_{i,t}$.

The first graph shows the response of expected simple returns to typical 25% cash-flow news. The typical 25% cash-flow news is induced by setting the VAR-error vector to a constrained maximum likelihood value, imposing the constraint that cash-flow news equals 0.25.

The second graph shows the response of institutional ownership to a typical 25% cash-flow news. The typical 25% cash-flow news is induced by setting the VAR-error vector to a constrained maximum likelihood value, imposing a constraint cash-flow news equals 0.25.

Dashed lines denote +/- 2 standard-error bounds, calculated using the jackknife.

Figure 1: Time−series evolution of variables

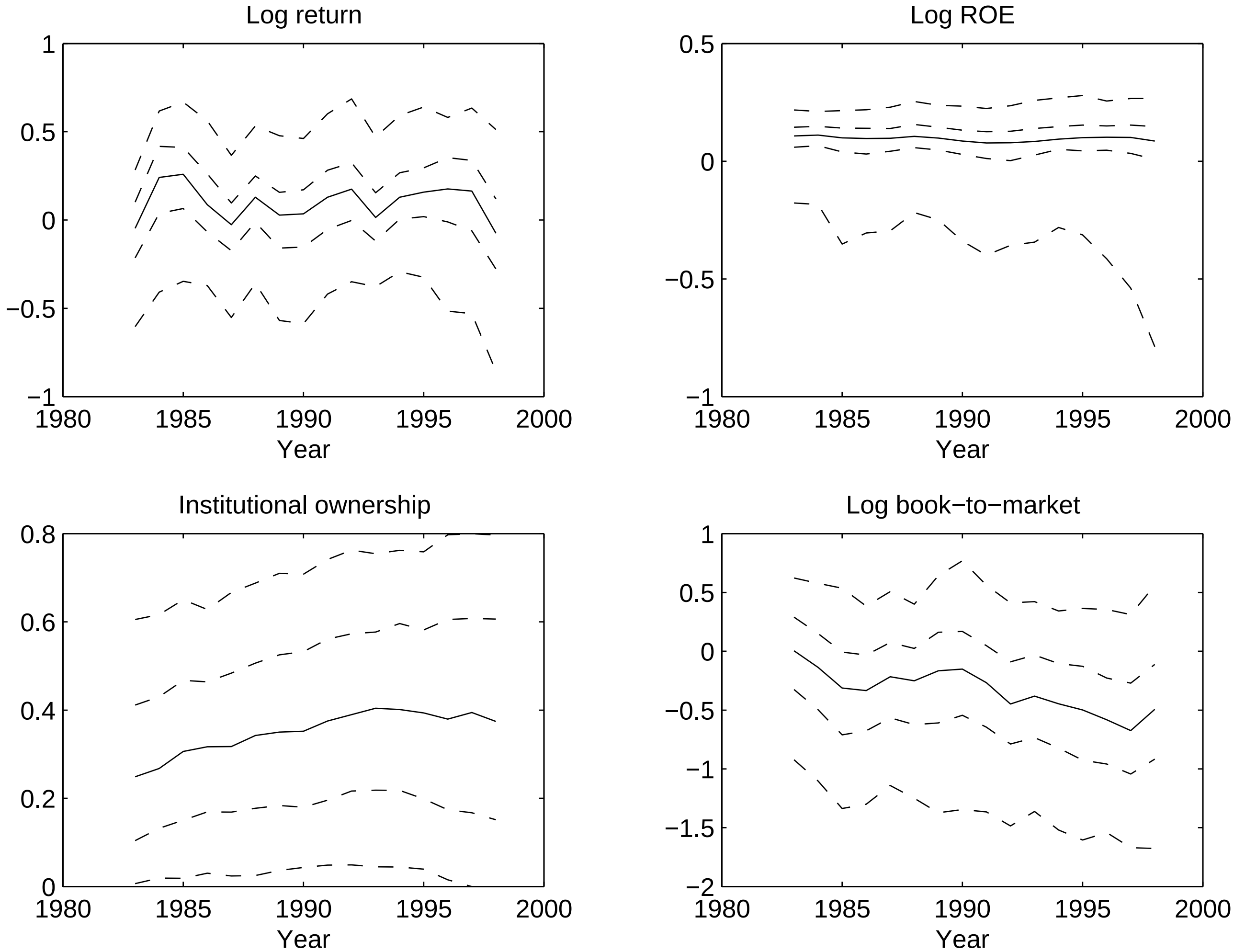


Figure 2: Price response to shocks

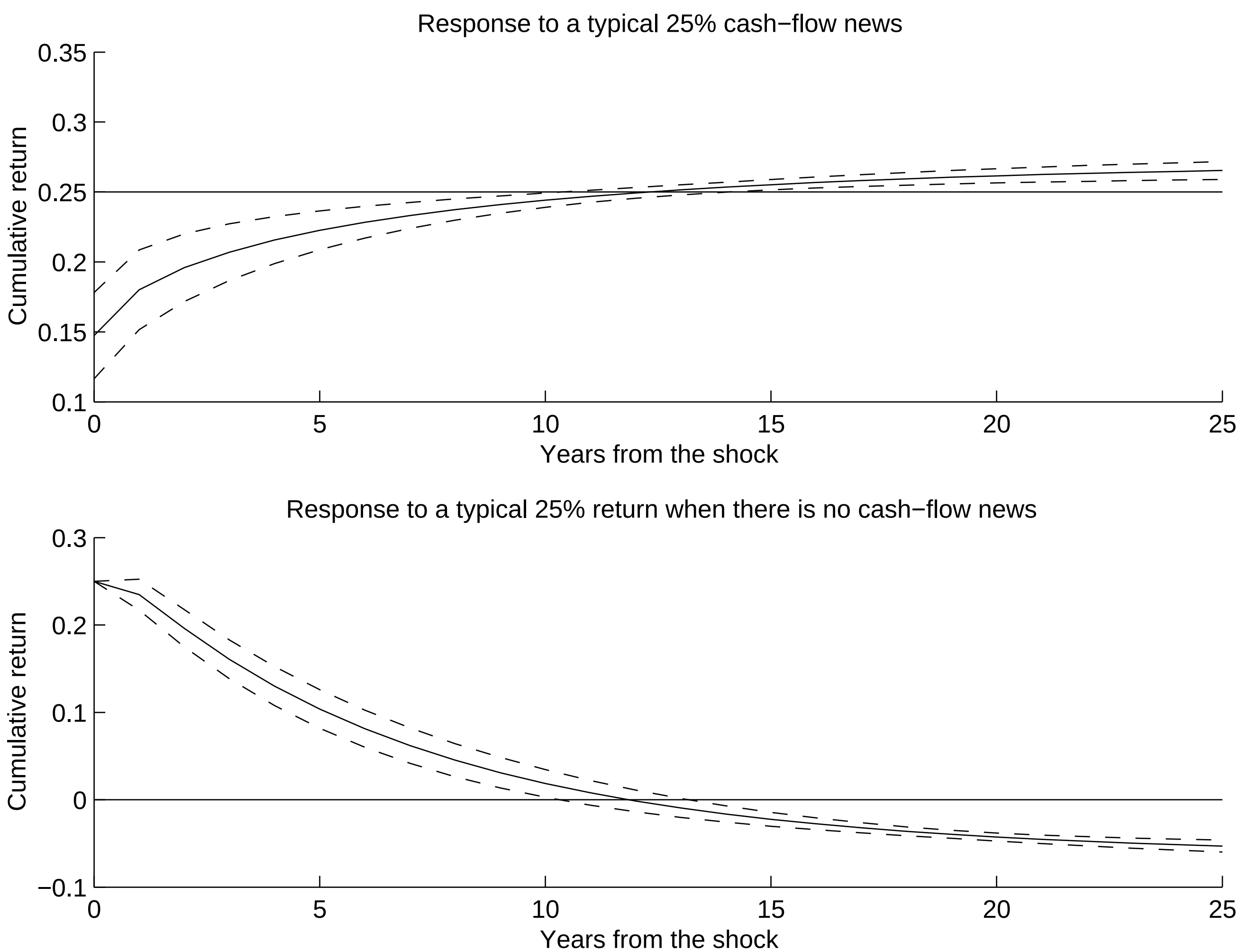


Figure 3: Response of institutional ownership to shocks

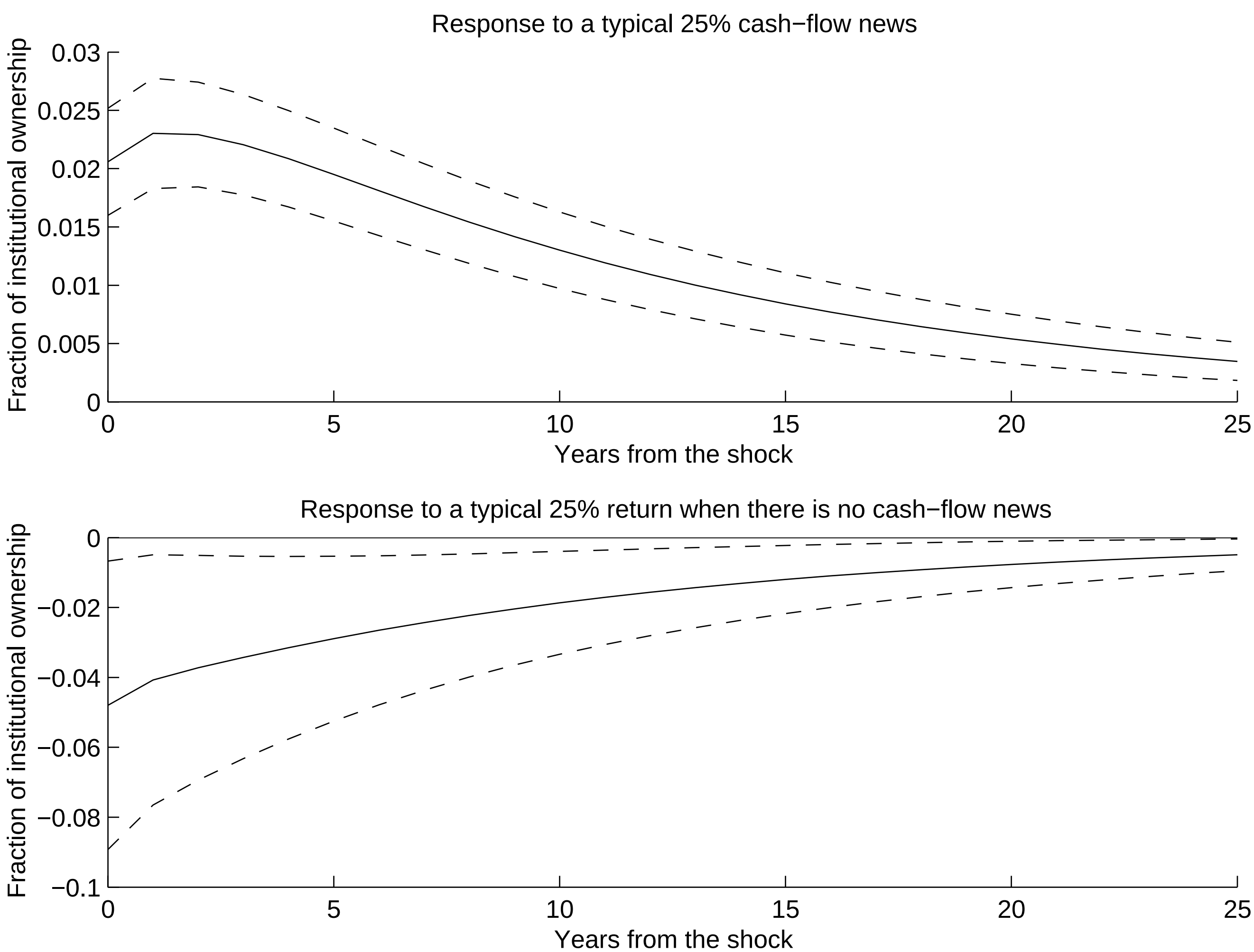


Figure 4: Results for size groups

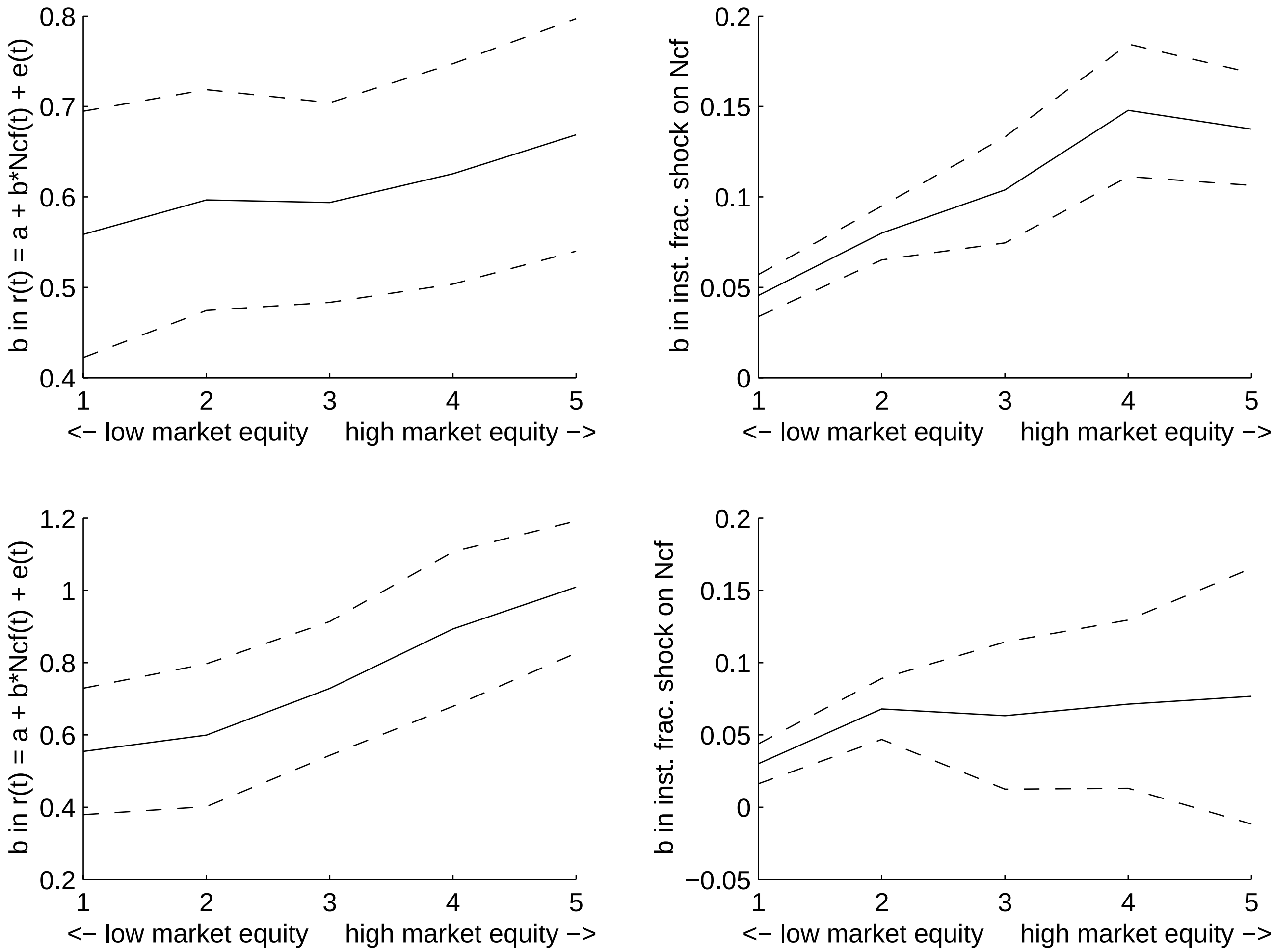
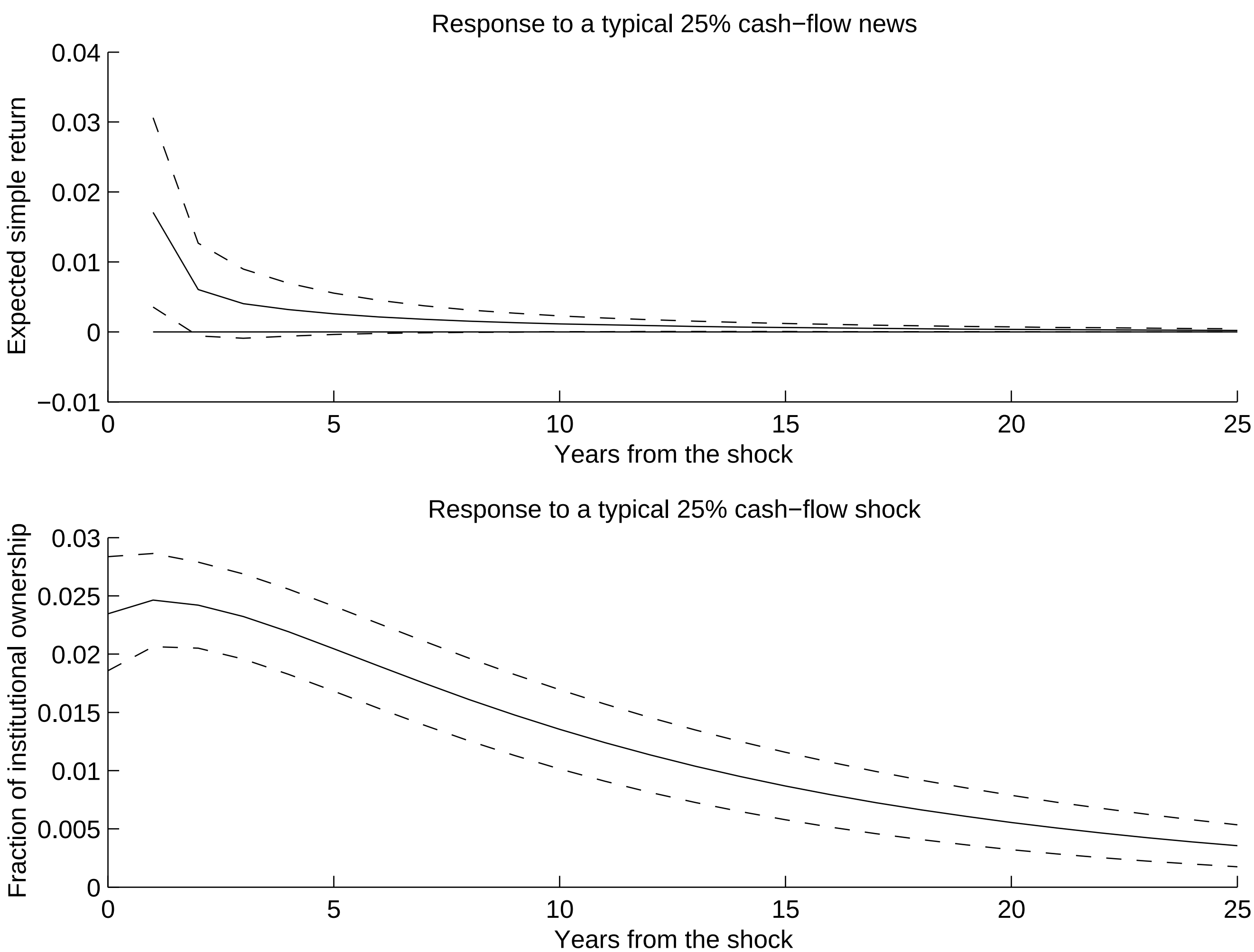


Figure 5: Impulse responses using simple returns and directly computed cash−flow news



[1] Bernard and Thomas (1989, 1990) study earnings surprises and Michaely, Womack, and Thaler (1995) dividend initiations and omissions. For a summary of empirical papers that find a drift subsequent to a public announcement, see Daniel, Hirshleifer, and Subrahmanyam (1998).

[2] Market-adjusted or benchmark-adjusted returns can be decomposed, as well. Apply equation (1) to individual firm-level stock return and market return separately, and subtract the latter equation from the former. As a result, the (unexpected) market-adjusted stock return can be decomposed into components due to above-market expected stock returns and ROEs. When the discussion applies only to market-adjusted quantities, we modify the notation by a tilde. For example, $\tilde{r}_t$ denotes the market-adjusted log stock return.

[3] In the case of market-adjusted returns and homogenous VAR, this typical risk premium is identically zero.

[4] The delisting-return assumptions follow Shumway's (1997) results. Shumway tracks a sample of firms whose delisting returns are missing from the CRSP data and finds that performance-related delistings are associated with a significant negative return, on average approximately -30 %. This assumption is unimportant to our final results, however.