Short-term Institutional Herding and Its Impact on Stock Prices

Andy Puckett
University of Missouri
Columbia, MO 65211
Phone: 573-884-5666
Email: puckettw@missouri.edu

and

Xuemin (Sterling) Yan*
University of Missouri
Columbia, MO 65211
Phone: 573-884-9708
Email: yanx@missouri.edu

Abstract

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JEL classification: G10; G11; G14
Keywords: Herding; Institutional investors; Return Reversal

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Abstract

Using the trades of 776 institutional investors from 1999 to 2004, we examine the existence and impact of short-term institutional herding. We report robust evidence of herding at the weekly frequency using the Lakonishok, Shleifer, and Vishny (1992) measure and the Sias (2004) measure. More importantly, we find that these weekly herds significantly affect the efficiency of security prices. We document strong evidence of return reversals following short-term sell herds and weak evidence of return continuations following short-term buy herds. Our results are consistent with short-term sell herds being motivated by behavioral considerations and driving asset prices away from fundamental values. Alternatively, the absence of return reversals following short-term buy herds suggest that these herds are information based and help impound new information into security prices.

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Institutional investing in the United States has increased dramatically over the last twenty-five years. Institutions now account for more than 60% of all equity ownership and an even greater percentage of the trading volume in U.S. markets (Schwartz and Shapiro (1992); Gompers and Metrick (2001); Jones and Lipson (2004); Boehmer and Kelly (2007)). This concentration of ownership and trading activity raises important questions for both academics and practitioners concerning the impact of institutional trading on securities prices.

Of particular interest is whether trading activity is correlated among institutions. Anecdotal evidence suggests that institutions herd together, and that these herds significantly impact stock prices. In a recent *Business Week* article, Margaret Popper states that "[t]he force of the herd pushes stock prices to extremes, producing short-term buying and selling frenzies … the market eventually snaps out of its panic, and ... readjusts to where valuations are fair." [1] Such institutional herds are often viewed as a short-term phenomenon, occurring over a period of days, and more importantly, are believed to temporarily drive security prices away from fundamental values.

Although academic research has investigated herding by institutions, most prior studies are constrained by the availability of public institutional data. As a result, these studies focus on institutional herding at quarterly or longer horizons.[2] Studies that use quarterly holdings data to investigate the existence, extent, and potential consequences of institutional herding lack power in detecting "herding in individual stocks at higher than quarterly frequencies" (Lakonishok,

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[1] Popper, Margaret. "Herd on the Street," *Business Week*, October 19, 2000.

[2] Publicly available data for institutional holdings are limited to quarterly 13F filings or mutual fund holdings reports, both of which provide a snapshot of institutional portfolios at quarterly intervals. The Securities Act Amendment of 1975 requires that institutional investors managing more than $100 million report their portfolio holdings to the Securities and Exchange Commission (SEC) on a quarterly basis (13F filings). Section 30 of the Investment Company Act of 1940 required mutual funds to report portfolio holdings at the end of each fiscal quarter. Beginning 1985, the SEC required that mutual funds report their holdings semiannually.

Shleifer, and Vishny (1992)). Indeed, contrary to views presented by the popular press, prior studies using quarterly or annual institutional ownership data (see, e.g., Nofsinger and Sias (1999); Wermers (1999); Sias (2004)) generally find evidence consistent with institutional herds moving stock prices toward (rather than away from) their fundamental values.

There are at least two reasons why the destabilizing effect of institutional herding, if it exists, may be more easily detected at a short-term horizon. First, the market's ability to absorb large trade imbalances engendered by institutional herds is more limited over shorter time horizons. If institutions involved in the herd must provide price concessions to counterparties to satisfy their demand for immediacy, such herds will result in larger transitory price impact. Second, if limits to arbitrage are more binding in the short-term (e.g., short-sale constraints), then deviations from fundamental values will be more likely to exist in the short-run, but dissipate over time due to the actions of arbitrageurs.

Studies using changes in quarterly holdings to measure institutional herding do not capture intra-quarter round-trip transactions and are not able to accurately identify the timing of trades.[3] In this study we address the data limitations of prior literature using a proprietary database of institutional trades to examine short-term institutional herding.[4] We find strong evidence of herding at a weekly horizon using both the Lakonishok, Shleifer, and Vishny (1992) measure and the Sias (2004) measure. In fact, the herding levels we document are higher than those found in previous studies using quarterly data. More importantly, we provide new evidence that short-term buy and sell herds have an asymmetric effect on the efficiency of equity

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[3] Elton, Gruber, Kransny, and Ozelge (2006) estimate that round-trip transactions account for approximately 20% of mutual fund managers' trades, and therefore represent a significant fraction of total trading volume.

[4] There is some evidence that actual intra-quarterly trading activity is significantly different than trading activity inferred from changes in quarterly institutional holdings. Boehmer and Kelly (2007) compare actual institutional trading using the NYSE's Consolidated Audit Trail Data (CAUD) to trading inferred from changes in 13F holdings during the period from 2000 to 2004 and find a statistically insignificant correlation of 0.04.

prices. We document strong evidence of return reversals following weekly sell herds and weak evidence of return continuations following weekly buy herds.

Using the Lakonishok, Shleifer, and Vishny (1992) herding measure, we find a mean herding level of 4.78% when at least two institutions trade a stock during a given week. The measure increases monotonically to 8.13% as we restrict the sample by requiring more institutions to trade a stock, suggesting that weekly herding is more prevalent in stocks where more institutions trade.[5] We also examine the existence of short-term herding using the Sias (2004) measure. Specifically, Sias (2004) investigates the temporal trading patterns of institutional investors to determine whether institutions follow the trades of other institutions. Consistent with Sias (2004) we find significant evidence of temporal dependence in institutional trading at the weekly horizon, and this dependence is driven by institutions following both their own trades and the trades of other institutions. The magnitude of our herding estimates (0.404) are almost four times as large as those reported by Sias (0.1197) who uses quarterly data. Our results strongly support the presence of weekly institutional herding.

Given our robust evidence regarding the existence of weekly institutional herding, we next investigate the impact of institutional herds on security prices. Institutional herds often result in intense buying and selling episodes, and these episodes may affect the efficiency of security prices. We investigate both the contemporaneous and subsequent abnormal returns of securities that institutional herds sell or buy.[6] The contemporaneous abnormal return for the portfolio of stocks intensely sold (bought) by institutional herds is -1.54% (1.85%). These

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[5] Lakonishok, Shliefer, and Vishny (1992) find that the quarterly herding measure declines from 2.7% to 2.1% as they restrict the sample by requiring up to 20 institutions to trade a stock in a given quarter.

[6] We calculate abnormal returns for each portfolio by subtracting the equal-weighted portfolio return for all sample stocks. This method is identical to the one used by Kaniel, Saar, and Titman (2008).

results are consistent with the hypothesis that institutional herds impact stock prices.[7] During the subsequent four week period, the portfolio of stocks *intensely sold* by institutional herds outperforms the portfolio of stocks *lightly sold* by institutional herds by an average of 0.36% per week. The return reversals we document support the popular press view that institutional herds exert temporary price pressures, causing prices to move below their fundamental value when institutional herds sell. Returns in the four week period following institutional buy herds are distinctly different than those for sell herds. The portfolio of stocks *intensely bought* by institutional herds earns average abnormal returns of 0.06% per week during the subsequent period. The absence of return reversals following weekly buy herds is consistent with these herds impounding new information into security prices.

We confirm our subsequent return results by implementing a series of four different robustness tests. First, we repeat our portfolio analysis separating the sample into firm-size quintiles. We find evidence of significant return reversals following weekly sell herds for all size quintiles, but find significant return continuations following weekly buy herds only for the smallest stocks. In addition, return reversals are larger for small stocks when compared to large stocks, which is consistent with the idea that the destabilizing effect of sell herds is greater in environments of constrained liquidity and arbitrage. Our second robustness test investigates pension plan sponsors separately in order to determine whether our initial results are driven by retail investor flows. Similar to Dasgupta, Prat, and Varanado (2007) we expect that pension plans are less likely than other institutions to be influenced by unexpected inflows/outflows of capital. Our results for pension fund managers are consistent with earlier (full sample) results.

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[7] An alternate explanation for our contemporaneous return results is that institutions are engaging in intra-week positive feedback trading.

Specifically, we continue to find evidence of return reversals following sell herds, and return continuations following buy herds.

Our third test investigates whether our results are robust to different abnormal return specifications. We calculate Fama-French (1993) 3-factor and Carhart (1997) 4-factor alphas for our institutional herding portfolios over the identical subsequent four-week period. We find that reversals following sell herds and continuations following buy herds are robust to both alternate specifications. Finally, we employ a multivariate framework and regress subsequent week stock returns on institutional herding variables. We control for numerous stock characteristics that may affect subsequent week returns including past stock returns and firm size. Consistent with our portfolio results, we find that sell herds are related to subsequent return reversals in all regression specifications. Buy herds are related to subsequent return continuations in five of our eight regression specifications. Overall, our robustness tests support the idea that buy herds are more likely to be information-based while sell herds are more likely to be driven by behavioral concerns.

While our finding that short-term sell herds destabilize asset prices differs from Nofsinger and Sias (1999), Wermers (1999) and Sias (2004), it is consistent with several concurrent working papers that focus on more recent time periods. Sharma, Easterwood and Kumar (2006) investigate internet stocks during the 1998 to 2001 bubble period and find evidence of return reversals in the quarter following buy herds. Brown, Wei, and Wermers (2007) study mutual fund herding following analyst upgrades/downgrades during the 1994 to 2003 sample period. They present modest evidence of return continuations in the first quarter following herding, but find that reversals are present when investigating returns after four quarters. Dasgupta, Prat and Verardo (2007) find that stocks that have been persistently purchased (sold) by institutions in the past four to five quarters underperform (overperform) over the next 12 to 30 months. Finally, our results are also consistent with San (2007) who investigates changes in institutional quarterly ownership and finds evidence of return reversals following intense institutional selling (individual buying) during the subsequent two year period.

Our study also relates to several studies in the price-impact literature. Kraus and Stoll (1972) and Chan and Lakonishok (1993, 1995) find that block or institutional purchases have a larger permanent price impact than block or institutional sells. These findings are consistent with our results that institutional buy and sell herds have an asymmetric impact on the efficiency of asset prices; however, our paper differs from this literature in several key aspects. First, the price impact literature focuses on individual trades, whereas we focus on aggregate (correlated) institutional trading. Second, the price impact literature documents little to no reversal after institutional sells, whereas we find significant price reversals after institutional sell herds.

Lastly, our paper is related to several recent studies examining the relation between individual or institutional trading and stock returns. Griffin, Harris, and Topaloglu (2003) examine the dynamics of institutional trading in Nasdaq 100 stocks and find a strong positive contemporaneous relation between institutional trading and stock returns. They attribute this relationship to positive-feedback trading, and find little evidence of return predictability at the daily frequency. Campbell, Ramadorai, and Schwartz (2007) apply a sophisticated algorithm to infer institutional trading from 13F filings and TAQ data. Consistent with our results, they find that institutional trading is negatively related to subsequent returns on a daily basis, and this negative relation is driven by institutional sells.

In some ways our paper provides an institutional analog to a study by Kaniel, Saar, and Titman (2008) who examine NYSE trading by individual investors during the 2000-2003 sample period. They find that individuals are contrarian traders, buying when prices decline and selling as prices increase. In addition, they find return reversals following intense individual buying and weaker evidence of return reversals following intense individual selling. Our results are consistent with Kaniel et al (2008) concerning return reversals following individual buying (i.e. institutional selling); however, our studies differ with respect to the modest return continuations that we find following institutional buy herds. Besides differences in sample period, stocks investigated, and source of trading data, we present one other possible explanation for this apparent discrepancy in findings. Kaniel et al (2008) are unable to observe individual trading that is internalized by brokerages or routed to wholesalers.[8] If brokerages are able to systematically internalize (or route to wholesalers) individual noise trades and send more informed order flow to the NYSE floor, then their measures of individual trading imbalance will reflect only the trading decisions of informed agents. Our study is not subject to this potential selection bias, since Abel Noser provides all trading activity for institutions in our sample.

The remainder of the paper proceeds as follows. The next section reviews the relevant literature on institutional herding. Section 2 discusses the data and our sample. Section 3 investigates the existence of weekly institutional herding. We examine the subsequent performance of securities following institutional herding in Section 4, and Section 5 concludes.

1. Related Literature

Theoretical herding models can broadly be broken into two categories: 1) herding that produces efficient prices and allows markets to impound information into asset prices more quickly than would otherwise occur, and 2) herding that potentially drives security prices beyond

[8] The fraction of individual trades that is unobserved is likely to be very large. Kaniel et al (2008) state that "Schwabb internalized 66% of its orders in the fourth quarter of 2003".

fundamental values, resulting in subsequent return reversals. In rational herding models, such as those proposed by Froot, Scharfstein, and Stein (1992) and Hirshliefer, Subrahmanyam, and Titman (1994), institutional investors receive correlated private information or infer information from each others' trades. As such, these rational herds (hereafter referred to as informational herds) aid in market efficiency.

Alternatively, institutions that trade with the herd because of non-informational (e.g. behavioral) reasons may cause asset prices to deviate from fundamental values. Scharfstein and Stein (1990) present a model where institutions may disregard their private information and trade with the herd due to the reputational risk of acting different from other institutions. They argue that since institutions are evaluated against each other, they have incentives to buy or sell the same stocks to avoid falling behind their peer group. In addition, institutional investors may herd due to fads or because they share preferences for stocks with certain characteristics, such as stocks with good prior performance or certain liquidity attributes (Banerjee (1992); Falkenstein (1996); Del Guercio (1996); Gompers and Metrick (2001)). When herding is driven by behavioral reasons and demand curves are not perfectly elastic, herding may destabilize stock prices, driving them away from the fundamental values.

Empirical studies using quarterly or annual institutional holdings data find moderate support for the existence of institutional herding. Lakonishok, Shliefer, and Vishny (1992) investigate contemporaneous institutional herding using quarterly holdings from 769 pension funds from 1985 to 1990 and find little evidence of herding in general and modest amounts of herding by institutions in small stocks. Using a similar methodology, Wermers (1999) finds modest levels of herding by mutual funds in large stocks, but does suggest that higher levels of herding are present when examining smaller stocks. Alternatively, Sias (2004) finds significant evidence of institutional herding by directly examining whether changes in institutional holdings are correlated over time.[9]

To differentiate between informational and behavioral herding, these studies focus on post-herding returns. Specifically, evidence of subsequent return reversal would be consistent with behavioral herding, while evidence of subsequent return continuation or the absence of return reversals would be consistent with herding driven by information. The above studies find no evidence to support the hypothesis that institutional herding destabilizes asset prices. Nofsinger and Sias (1999), Wermers (1999), and Sias (2004) all provide evidence that asset prices continue in the direction of the herd during subsequent periods. Nofsinger and Sias (1999) find a significant positive relation between changes in institutional ownership and subsequent stock returns at an annual frequency. Wermers (1999) finds that stocks institutional herds buy outperform the stocks that institutional herds sell during the subsequent four quarters. Similarly, Sias (2004) finds a significant positive relation between institutional demand and subsequent stock returns at the quarterly frequency. These results support the contention that herding helps drive asset prices to fundamental values more quickly than would otherwise occur.[10]

All herding studies that we are aware of use publicly available quarterly (or annual) institutional holdings data to investigate herding. As such, they have limited power when investigating institutional trading patterns that occur over shorter time intervals. If herding is likely to be a short-term phenomenon as suggested by anecdotal evidence, such studies may understate both the extent and effects of institutional herding. One study attempts to circumvent

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[9] Other studies investigating herding include Brown, Wei and Wermers (2007) and Wylie (2005). Wylie (2005) finds that LSV herding metrics are positively biased due to short-sale constraints. After adjusting the measure, he finds no significant evidence of herding in U.K. stocks.

[10] As discussed previously, studies by Sharma, Easterwood, and Kumar (2006), Brown, Wei, and Wermers (2007), and Dasgupta, Prat, and Verardo (2007) provide some evidence that institutional herding activities may be destabilizing.

this problem using more frequent data. Dennis and Strickland (2002) investigate days when the absolute value of returns for the equal- or value-weighted CRSP market index is greater than 2%. They find that stocks with high levels of institutional ownership experience more extreme returns and abnormal volume than stocks with low levels of institutional ownership. They also find that such stocks exhibit return reversals over the subsequent six month period following large down movement days in the CRSP index. They argue that institutional investors are herding together and buying (selling) stocks on large up (down) movement days, and conclude that this herding drives stock prices away from fundamental values.

Although Dennis and Strickland (2002) make progress toward identifying institutional behavior over shorter time periods, they must infer this intra-quarterly behavior using quarterly 13F filings. In addition, Dennis and Strickland (2002) condition their study on periods of extreme market turmoil. As such, their study is limited in its ability to provide insights into the overall existence (or lack thereof) of institutional herding. We contribute to the existing body of herding literature by investigating the existence and effects of short-term institutional herding using actual institutional trading data.

2. Data and Sample

We obtain institutional trading data from the Abel Noser Corporation. Abel Noser is a widely recognized consulting firm that works with institutional investors to monitor their equity trading costs.[11] Abel Noser clients include pension plan sponsors such as the California Public Employees' Retirement System (CalPERS), the Commonwealth of Virginia, and the YMCA

[11] Abel Noser provides consulting services for equity trading costs in a manner similar to the Plexus Group, whose data has been used extensively in academic studies. Other studies that have used Abel Noser data include Goldstein, Irvine, Kandel, and Weiner (2008), Chemmanur and Hu (2007), and Lipson and Puckett (2007).

retirement fund, as well as money managers such as MFS (Massachusetts Financial Services), Putman Investments, Lazard Asset Management, and Vanguard.[12] The Abel Noser sample of institutional trades contains trades from 776 institutions and covers the period from January 1, 1999 until December 31, 2004.

Summary statistics for Abel Noser trade data are presented in Panel A of Table 1. Institutions in the Abel Noser database are responsible for approximately 68 million trades (reported executions) which represent approximately 8% of total CRSP daily trading volume (in dollars) during the 1999 to 2004 sample period.[13] For each execution Abel Noser provide 107 different variables. Our study uses six of these variables including the institution identity code, date of execution, stock traded, number of shares executed, execution price, and whether the execution is a buy or sell. The identity of the institution is not provided to us for privacy reasons; however, the unique identity codes allow us to distinguish between different portfolio manager's trades both in the cross-section and through time.[14] The total number of different stocks traded by institutions varies from 4,692 in 2002 to 6,150 in 1999. Summary statistics show that the mean shares per execution varies from 7,276 in 2004 to 11,159 in 2001, while the median ranges from 700 shares in 2004 to 1,700 shares in 1999. Over the entire sample period, Abel Noser institutional clients traded more than 628 billion shares, representing more than $18.9 trillion worth of stock trades.

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[12] The Abel Noser data contain trades for three institutions classified as "brokers". These institutions are excluded from our analysis since we are unable to discern whether these trades represent market-making activities by the brokerage firm, or trades for the brokerage firm's own account.

[13] We calculate the ratio of Abel Noser trading volume to CRSP trading volume during each day of the sample period. We include only stocks with sharecode equal to 10 or 11 in our calculation. In addition, we divide all Abel Noser trading volume by two, since each individual Abel Noser client constitutes only one side of a trade. We believe this estimate represents an approximate lower bound for the size of the Abel Noser database.

[14] Identifying variables also include summary execution costs for ticket orders which often include multiple executions. These variables include the share-weighted execution costs and total number of shares executed in the ticket.

We face a tradeoff when choosing the time horizon to investigate institutional herding. The objective of our analysis is to study herding behavior at a short-term frequency. Analysis at a daily frequency does not allow for a reliable measure of herding in many small stocks, since only a small number of institutions may trade these stocks during a given day. At a weekly interval, we find that the mean number of institutions trading each stock is between 7.11 (in 1999) and 11.67 (in 2004). The median number of institutions trading a stock each week is between 4 and 8. Therefore, we decide to investigate institutional herding at the weekly frequency.[15] We begin by creating a weekly time series of institutional trades.[16] We require that a minimum of two institutions trade a stock in a given week for the observation to be included in our empirical analysis, since, by definition, herding involves more than one institution. For each stock traded by institutions in the Abel Noser dataset, we collect information on shares outstanding, returns, and volume from the CRSP database. We include in our sample only those securities with a CRSP sharecode of 10 or 11. We collect the book value of equity for each security traded from the Compustat database.

We report summary statistics for our sample of stocks in Panel B of Table 1. Specifically, we present the time-series mean, median, standard deviation, maximum, and minimum of weekly cross-sectional averages. The mean market capitalization of securities traded by Abel Noser institutions is $4.69 billion, while the average share price is $54.36. These results are consistent with institutional preference for large and liquid stocks documented in prior literature (Gompers and Metrick (2001)). In addition, we find that these stocks exhibit a mean

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[15] Our choice of time horizon is consistent with Kaniel, Saar, and Titman (2007), who examine the impact of individual trades at a weekly frequency.

[16] The weekly time series is constructed from Wednesday close to Wednesday close in order to avoid any bias associated with the weekend effect.

book-to-market ratio of 0.50, and during an average trading week 18% of all sample stocks belong to the S&P 500 index.

3. Institutional Herding at a Weekly Frequency

In this section, we examine the existence and extent of institutional herding at a weekly frequency. We use two herding measures. The first measure is proposed by Lakonishok, Shleifer, and Vishny (1992) and has been widely used in the herding literature. The second measure was recently developed by Sias (2004), who exploits the idea that herding implies that institutions follow each other into or out of equity positions.

A. LSV Herding Measure

If institutions herd, then a disproportionate number of institutions should be buying (selling) a security over the defined time period. In order to test for the existence of such activities, Lakonishok, Schleifer and Vishny (1992) (hereafter referred to as LSV) develop the following herding metric ($H_{k,t}$):

$$H_{k,t} = \left| Raw\Delta_{k,t} - \overline{Raw\Delta_t} \right| - E\left| Raw\Delta_{k,t} - \overline{Raw\Delta_t} \right| \qquad (1)$$

where

$$Raw\Delta_{k,t} = \frac{Number\ of\ Institutions\ Buying_{k,t}}{Number\ of\ Institutions\ Buying_{k,t} + Number\ of\ Institutions\ Selling_{k,t}} \qquad (2)$$

$H_{k,t}$ is a measure of herding for stock k at time t, $\overline{Raw\Delta_t}$ is the average $Raw\Delta_{k,t}$ measure for all stocks at time t, and $E\left|Raw\Delta_{k,t} - \overline{Raw\Delta_t}\right|$ is the adjustment factor.[17] The inclusion of $\overline{Raw\Delta_t}$ in equation (1) controls for aggregate shifts into or out of stocks during a particular week, while the

[17] Details about the computation of the adjustment factor are available on request.

adjustment factor accounts for the fact that the first term in equation (1), which is an absolute value, is always greater than zero. Under the null hypothesis of no herding, we expect the metric $H_{k,t}$ to be insignificantly different from zero.

We calculate the LSV measure of institutional herding at a weekly frequency for all stock-week observations where at least two institutions trade, and present results in Table 2. The average LSV herding measure for stocks with at least two institutions trading is 4.78%. Assuming that, on average, half of the institutions buy (or sell) any given security, one can interpret the above number as suggesting that 54.78% of institutions were trading in one direction, while the remaining 45.22% were trading in the opposite direction.[18] Panel A of Table 2 also presents the mean LSV herding measure for stock-week observations when at least five, ten, twenty-five, or fifty institutions trade. In order to compare our results with prior studies we concentrate our analysis on weeks when at least five institutions trade a particular stock (Brown, Wei, and Wermers (2007)). When at least five institutions trade a security in a given week, we find that the average herding measure is 4.95%, which is slightly larger than that reported by previous studies using quarterly ownership data (Lakonishok, Shleifer, and Vishny (1992); Wermers (1999)).[19] The measure increases monotonically to 8.13% as we restrict the sample by requiring 10, 25 or 50 institutions to trade a specific stock in a given week. These results are distinctly different from those presented by Lakonishok, Shleifer, and Vishny (1992) who find that the quarterly herding measure declines from 2.7% to 2.1% when they restrict the sample by

[18] The construction of the LSV measure does not allow by itself interpretation regarding the direction of herding activity.

[19] Lakonishok, Shliefer and Vishny (1992) report a mean herding measure of 2.0% when stocks are traded by at least 10 managers, while Wermers (1999) reports a mean herding measure of 3.4% when at least five funds traded the stock. Brown, Wei, and Wermers (2007) suggest that average herding may have increased over time, and find mean herding of 4.39% during the 1994 to 2003 sample period.

requiring 20 institutions to trade a stock in a given quarter. Our results suggest that weekly herding is more prevalent in stocks where more institutions trade.

Following existing literature, we test whether the level of LSV herding differs across firm-size quintiles. If herding is motivated by private information, we may expect higher levels of herding in smaller stocks where the publically available information environment is more limited. To investigate this relationship we divide stocks into market capitalization quintiles during each trading week and report the mean level of LSV herding for each quintile in Panel B of Table 2. Again, we require all stock-week observations to have at least two institutions trading. We find that herding is higher (6.96%) in small stocks when compared to large stocks (4.98%). The difference of 1.99% is statistically significant at the 1% level, and is consistent with Lakonishok, Shleifer, and Vishny (1992) and Wermers (1999) who find higher levels of herding in smaller stocks using quarterly data. However, we are cautious about the interpretation of our results since the level of herding does not display a monotonic relationship across all firm-size quintiles.

B. Sias (2004) Herding Measure

Herding occurs when institutions' trading patterns are correlated. If institutions follow other institutions into or out of the same stocks, or if institutions follow their own trades, then the fraction of institutions buying ($Raw\Delta_{k,t}$) this week will be positively correlated with the fraction of institutions buying last week. Prior literature frequently uses the LSV metric of herding which accounts for the contemporaneous number of buyers and sellers in a given security; however, the LSV measure does not directly examine the temporal pattern in the cross-section of institutional trading. Sias (2004) is the first to recognize the importance of this cross-sectional temporal dependence in understanding institutional herding. He investigates the correlation between the fraction of institutions increasing their portfolio weights this quarter and last quarter.

We follow Sias (2004) to investigate the temporal dependence of institutional herding by estimating the following regression:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t} \tag{3}$$

where

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})} \tag{4}$$

Equation (4) standardizes $Raw\Delta_{k,t}$ to have zero mean and unit variance to allow for meaningful comparison over time. In regression equation (3) we specify $\Delta_{k,t}$ as a function of prior week $\Delta_{k,t-1}$.[20] Since all dependent and independent variables are standardized to have zero mean, there is no intercept in the regression equation. According to Sias (2004), if institutions herd, then the coefficient β_t should be positive and significant.

We estimate regression equation (3) each week and use the mean and standard deviation of time series coefficients to determine significance (Fama and MacBeth, 1973). Coefficient estimates are reported in the first column of Table 3, and consistent with Sias (2004) we find strong evidence that institutions are following themselves and/or other institutions into or out of the same stocks. Our coefficient estimate for β_t is 0.404 and is almost four times as large as the coefficient estimate that Sias reports using quarterly data (β_t=0.1197).[21] The coefficient is

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[20] In untabulated robustness tests we include the lagged return variable to control for an institution's propensity to engage in positive-feedback trading (Grinblatt, Titman, and Wermers (1995); Badrinath and Wahal (2002); Bennet, Sias, and Starks (2003)). Controlling for past returns does not change, either qualitatively or quantitatively, the result that institutional demand is significantly positively related to lagged institutional demand.

[21] We are able to directly compare our coefficient estimates to those reported by Sias (2004) since both studies standardize dependent and independent variables to have zero mean and unit variance.

significant at the 1% level, and can be interpreted as the cross-sectional correlation between institutional demand this week and last week. Similar to our LSV herding level results, the magnitude of the coefficient estimate increases to 0.563 as we restrict the sample by requiring five, ten, twenty-five, or fifty institutional traders. In addition, the average R-squared in our regression (16.79%) is almost an order of magnitude larger than that reported by Sias (2.38%).

The strength of coefficient estimates suggests that institutional herding is stronger at the weekly level than at the quarterly level. However, regression equation (3) does not differentiate between the two alternate hypotheses that 1) institutions are following their own trades, or 2) institutions are following the trading patterns of other institutions. This distinction is particularly important at weekly intervals since positive serial correlations may reflect position decisions that institutions implement over multiple trading days as a result of market conditions or implementation difficulties (Lipson and Puckett, 2007). In order to flesh out these two alternate hypotheses we follow Sias (2004) and decompose the slope coefficient β_t into two parts: 1) institutions following their own trades, and 2) institutions following others' trades.[22] We present the partitioned slope coefficients and associated *t*-statistics in columns two and three in Table 3. Our findings suggest that for the sample of stock-week observations with at least two institutions trading, on average 42% (=0.171/0.404) of the β_t coefficient estimate results from institutions following their own trades. Conversely, 58% (=0.234/0.404) of the coefficient estimate is due to institutions following the trades of other institutions.

Interestingly, as we require more institutional traders, the partitioned slope coefficient for institutions following their own trades decreases, while the partitioned slope coefficient for institutions following others' trades increases. In the sample of stock-week observations where

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[22] We decompose the β_t coefficient using the same decomposition methodology used by Sias (2004). We refer readers to pp. 174-175 in Sias (2004) for a more detailed account of this methodology.

at least fifty institutions trade, on average 9% (=0.051/0.563) of the β_t coefficient estimate comes from institutions following their own trades and 91% (0.512/0.563) is due to institutions following others' trades. Consistent with Sias (2004) we interpret our results as strong evidence of weekly institutional herding.

4. Institutional Herding and Stock Performance

In the previous section, we find strong evidence of institutional herding at a weekly frequency. In this section, we investigate the effect of weekly institutional herding on asset prices. When institutions herd together and buy (sell) a stock during a particular week, such herding may be either stabilizing or destabilizing for security prices. If herding is primarily information based, the price adjustment will be permanent. Further, if the price adjustment is incomplete, prices will continue in the same direction as the herd (Wermers (1999); Sias (2004)). However, if short-term herding is not information based and occurs for behavioral reasons, such herds may drive asset prices away from fundamental values. In such situations, one expects to find evidence of return reversals in the subsequent period.

Institutional herds may engender large trading imbalances. We expect that a herd's effect on asset prices is a function of the aggregate net amount traded. Similar to Nofsinger and Sias (1999), in order to capture both the magnitude and direction of these herds we measure herding intensity as the total weekly institutional trade imbalance (normalized by shares outstanding). We reiterate that, on average, between 7.11 and 11.67 institutions trade a stock for each of our stock-week observations, thus it is unlikely that our measure will be systematically dominated by a single large trader.[23] We proceed as follows: for each stock-week observation we require at least two institutional traders. Each week we separate all sample stocks into buy and sell categories (based on aggregate institutional trade imbalance), and within each category divide the sample into trade imbalance quintiles. This procedure results in ten portfolios, where portfolio 1 (portfolio 5) is the *intense sell* (*light sell*) herding portfolio, and portfolio 10 (portfolio 6) is the *intense buy* (*light buy*) herding portfolio.

A. Prior and Contemporaneous Stock Returns

We first investigate contemporaneous and prior week returns surrounding herding activity. Following Kaniel, Saar, and Titman (2008) we calculate the abnormal return for each portfolio by subtracting the return on a market proxy (the equal-weighted portfolio of all sample stocks). Abnormal returns for each portfolio during weeks -4 to 0 (where 0 is the portfolio formation period) are presented in Table 4. Consistent with prior literature on positive feedback trading (e.g., Grinblatt, Titman, and Wermers, 1995), we find negative abnormal returns of -1.03% in the week preceding *intense sell* herds, and positive abnormal returns of 0.64% in the week preceding *intense buy* herds. Portfolio returns for each of the four weeks preceding portfolio formation are significantly different between *intense buy* and *intense sell* herds. The difference is monotonically increasing as we move from week -4 (0.31%) to week -1 (1.66%).

Not surprisingly, we also find the contemporaneous (week 0) abnormal return is positively related to both the direction and intensity of the herd. Stocks in the *intense sell* portfolio experience negative contemporaneous abnormal returns of -1.54%, while those in the *intense buy* portfolio have positive contemporaneous abnormal returns of 1.85%. Our results are consistent with the hypothesis that institutional herds impact stock prices; however, we are

[23] In untabulated robustness tests we run our analysis using the LSV herding measure as the conditioning variable for tests involving subsequent returns. Results are qualitatively similar to those reported in this paper.

cautious in our interpretation of these results. Our methodology does not allow us to differentiate between the competing hypotheses that 1) the price impact of institutional herds drives these return relationships, or 2) institutions are merely engaging in intra-week positive feedback trading.

B. Subsequent Stock Returns

To investigate the impact of institutional herds on asset prices we examine returns for all portfolios over the subsequent four weeks. Portfolios are rebalanced each week and held for one to four weeks. Our approach is similar to that of Jegadeesh and Titman (1993) in their examination of momentum effects. Following Jegadeesh and Titman, we use a calendar-time approach to calculate average weekly portfolio returns. Furthermore, we use Newey-West standard errors to conduct statistical inferences.

We present the subsequent period abnormal returns for all herding portfolios in Table 5. *Intense sell* portfolios outperform *intense buy* portfolios by an average of 0.20% (*t*-statistic=3.62) per week during the four weeks following these intense herding episodes. Initial results suggest that there is evidence of return reversals following short-term institutional herding activity, however, upon closer investigation we find evidence of an asymmetry between buy and sell herds.

The portfolio of stocks *intensely sold* by institutional herds significantly outperforms the portfolio of stocks *lightly sold* by institutional herds over the entire four week period. This performance difference is highest in the first week following portfolio formation, where we find the *intense sell* portfolio earns 0.39% while the *light sell* portfolio return is -0.19%. The difference of 0.58% is significant at the 1% level. In addition, the average weekly return difference during the four weeks is 0.36% and still highly statistically significant. Our results suggest evidence of reversals following short-term intense sell herds.

Evidence from the performance following buy herds displays remarkably different characteristics than that of sell herds. We find that the *intense buy* stocks outperform the *light buy* stocks by an average of 0.16% (*t*-statistic=2.24) during the four weeks following portfolio formation. Again, this difference is largest in the first week following herding activity, where the *intense buy* portfolio returns are 0.15% versus the *light buy* portfolio returns of -0.15%. Our results suggest a modest return continuation following short-term intense buy herds.

Our results are quite apparent when illustrated graphically as in Figure 1, which plots the cumulative abnormal returns over the period from week -4 through week 12. Figure 1 indicates that stocks that herds buy outperform the stocks that herds sell prior to and during the week of portfolio formation. More importantly, the graph makes it abundantly clear that *intense sell* herds are followed by return reversals while the contemporaneous returns associated with *intense buy* herds are permanent.

Our results for weekly sell herds are consistent with such herds pushing prices lower than their fundamental values, thereby causing higher subsequent returns. Alternatively, it appears that weekly buy herds are accompanied by a permanent change in stock price. These results contrast with those found by Nofsinger and Sias (1999), Wermers (1999), and Sias (2004), who find a symmetric positive relation between institutional herding and subsequent stock performance. Our results on the effect of sell herds are consistent with Sharma, Easterwood, and Kumar (2006), Brown, Wei, and Wermers (2007), and Dasgupta, Prat, and Verardo (2007) who find some evidence that institutional herds destabilize asset prices, and are also consistent with anecdotal evidence that short-term institutional herding destabilizes security prices.[24] We note that a critical difference between prior studies and our study is that we examine institutional herding at a weekly, rather than the quarterly or annual horizon.

C. Robustness Tests

C.1. By Firm Size

In Table 6, we repeat the portfolio analysis separating the sample by firm size. To the extent that smaller firms are less liquid and are subject to greater arbitrage constraints, we expect short-term institutional sell herds to have a greater destabilizing impact on smaller stocks. Each week we separate firms into quintiles based on firm size. For each size quintile, we divide weekly observations into buy and sell categories, and within each category divide the sample into trade imbalance quintiles (similar to Table 5). The process results in fifty portfolios for each trading week. We then measure abnormal portfolio returns for four weeks following portfolio formation.[25] Due to the volume of data that results from these tests, we report only the performance of the *intense sell* minus *light sell*, *intense buy* minus *light buy*, and *intense buy* minus *intense sell* portfolios (and associated *t*-statistics) for each size quintile in Table 6.

For every size quintile we find *intense sell* portfolios significantly outperform *light sell* portfolios, suggesting evidence of significant return reversals. Further, we find that the return difference between *intense sell* and *light sell* is monotonically decreasing in firm size. That is, we find reversals are larger for small stocks (0.76%) when compared to large stocks (0.16%) for

[24] Our results are also consistent with Dennis and Strickland (2002), who find some evidence of return continuations for high institutional ownership firms following large up movement days in the CRSP index, and return reversals for high institutional ownership firms on large down movement days in the CRSP index. They attribute these return patterns to institutional herding.

[25] We also compute raw returns, Fama-French 3-factor alphas, and Carhart 4-factor alphas. Results using these measures are similar in magnitude and significance to those reported in Table 6.

the four-week holding period. Our results are consistent with the idea that the destabilizing effect of sell herds is greater in environments of constrained liquidity and arbitrage.

Panel B reports that *intense buy* portfolios outperform *light buy* portfolios for each size quintile and for each holding period. These differences are all positive but only significant for the smallest two size quintiles over the entire four week holding period. The average weekly return difference between *intense buy* and *light buy* portfolios is 0.25% (t-statistic=3.19) for the smallest quintile of stocks, and 0.05% (t-statistic=0.53) for the largest stock quintile. Overall, we find no evidence of return reversals following institutional buy herds. The evidence of return continuations for the smallest two quintiles of stocks suggests that information is only gradually impounded into stock prices for the smallest stocks. This finding is also consistent with the premise that large institutional orders in smaller stocks are often executed over multiple days (Lipson and Puckett (2007)). If weekly herding activity is positively autocorrelated due to implementation difficulties (i.e. for smaller stocks) we would expect returns to continue in the same direction as the herd in subsequent weeks.[26]

C.2. Pension Plan Sponsors

To the extent that correlated fund flows may drive institutional herding (Sias (2004)) and fund flows are related to future stock returns (Frazzini and Lamont, 2007), our results may be driven by exogenous liquidity shocks to fund managers from retail investors. In order to address this concern, we employ a methodology similar to Dasgupta, Prat and Varanado (2007) and exclude institutions most likely to be influenced by unexpected inflows and outflows of capital.

[26] In other robustness tests we investigate whether subsequent portfolio returns differ by exchange. Consistent with full sample results we find evidence of return reversals following institutional sell herds and return continuations following institutional buy herds for both NYSE/AMEX and Nasdaq stocks. We note that evidence of return reversals for Nasdaq stocks is stronger than reversals among NYSE/AMEX stocks. Our findings alleviate concerns that our results are driven by technology stocks traded on the Nasdaq.

Specifically, the Abel Noser database contains trades from both pension plan sponsors and money managers. Consistent with prior literature, we expect that pension fund managers are unlikely to experience unexpected shocks in fund flows. We repeat our initial analysis (similar to Table 5) using only the trades of pension fund managers and require at least two pension fund managers trading for each stock-week observation in our analysis. Our results are presented in Table 8, and are consistent with earlier (full sample) results. *Intense sell* portfolio stocks outperform *light sell* portfolios by 0.66% in the first week following sell herds, and by an average of 0.34% a week during the four weeks following herding activity. Also, consistent with prior results, the *intense buy* portfolio outperforms the *light buy* portfolio by 0.20% in the first week following herding activity, and by an average of 0.13% per week for the first four weeks following herding activity. Overall, our results for pension plan sponsors suggest that our initial findings are unlikely to be driven by investor fund flows.

C.3. Multi-Factor Abnormal Returns

We next investigate whether our results (presented in Table 5) are robust to different abnormal return specifications. We calculate both Fama-French (1993) 3-factor and Carhart (1997) 4-factor portfolio alphas over the same subsequent four week period. Our estimation uses the following regressions:

$$r_{p,t} = \alpha_p + \beta_{1,p} RMRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + e_{p,t} \qquad (5)$$

$$r_{p,t} = \alpha_p + \beta_{1,p} RMRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + e_{p,t} \qquad (6)$$

Where, $r_{p,t}$ is the weekly excess return on a portfolio of stocks; *RMRF* is the excess return on the value-weighted market portfolio; and *SMB*, *HML*, and *UMD* are returns on zero-investment factor-mimicking portfolios for size, book-to-market, and one-year momentum in stock returns.

The weekly Fama-French and Carhart factors are computed based on daily factors downloaded from Kenneth French's Website.[27]

Results are robust to both alternate specifications. Panel A shows that Fama-French 3-factor alphas (equation 5) are 0.56% higher for the *intense sell* portfolio when compared to the *light sell* portfolio in the week immediately following herding activity. The average weekly return difference continues to be significant for four weeks following short-term sell herding (0.34% per week, *t*-statistics=6.50). Also, consistent with prior results, the *intense buy* portfolio outperforms the *light buy* portfolio by 0.27% in the first week following herding activity, and by an average of 0.15% per week for the subsequent four weeks. Results are strikingly similar in Panel B when investigating Carhart 4-factor alphas (equation 6). The one week difference between *intense buy* and *light buy* (*intense sell* and *light sell*) portfolios is almost identical to that reported in Panel A with 0.26% (0.58%).

C.4. Cross-Sectional Regressions

Although portfolio return analysis overwhelmingly supports the existence of return reversals following intense sell herds and modest return continuation following intense buy herds, we test the robustness of our findings in a multivariate regression framework. We implement the following regression model in our analysis:

$$\begin{aligned} RET_{k,t,t+n} &= \alpha + \beta_1 IntenseBuy_{k,t} + \beta_2 IntenseSell_{k,t} + \beta_3 RET_{k,t-5,t-1} + \beta_4 MVE_{k,t-1} \\ &+ \beta_5 AGE_{k,t-1} + \beta_6 StdDev_{k,t-5,t-1} + \beta_7 Price_{k,t-1} + \beta_8 BM_{k,t-1} + \beta_9 SP500_{k,t-1} + e_{k,t} \end{aligned} \tag{7}$$

where the dependent variable is the cumulative future return of stock *k*. We measure future returns over 1, 2, 3, and 4 week periods and present results for all regression specifications in Table 9. To investigate the relationship between subsequent returns and herding activity, we

[27] Kenneth French's Website is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

include the dummy variable *IntenseBuy* (*IntenseSell*) which equals 1 if the stock is in the *intense buy* (*intense sell*) portfolio. We also include the prior four week security return ($RET_{k,t-5,t-1}$) to control for the existence of return autocorrelation. Similar to previous cross-sectional regressions (e.g., Gompers and Metrick (2001)) we include variables for the lagged log of firm size ($MVE_{k,t-1}$), the lagged log of firm age ($AGE_{k,t-1}$), the lagged log of return volatility ($StdDev_{k,t-5,t-1}$), and a dummy variable for S&P 500 index membership ($SP500_{k,t-1}$). In addition, we control for the lagged log of share price ($Price_{k,t-1}$) and the lagged book-to-market decile of the firm ($BM_{k,t-1}$).

We run the regression for each week of our sample period and report the time series mean regression coefficient using the Fama and MacBeth (1973) approach in Panel A of Table 9. Across all regression specifications we find that future stock returns are positively related to both *IntenseBuy* and *InstenseSell* dummy variables. The magnitude of coefficients for the *IntenseBuy* dummy variable ranges from 0.149 to 0.307 and is significant in five of the eight regression specifications. The coefficient estimate for the *IntenseSell* dummy variable ranges from 0.338 to 0.907 and is significant at the 1% level in all eight regression specifications. The positive coefficients indicate the existence of return reversals following weekly *intense sell* herds and return continuation following weekly *intense buy* herds. Further, the effect of return reversals after intense sell herds is stronger than the effect of return continuation after institutional buy herds. All findings are consistent with our earlier portfolio results. Findings also indicate that subsequent 1, 2, 3, and 4 week returns are negatively related to prior period returns ($RET_{k,t-5\ to\ t-1}$) and firm size ($MVE_{k,t-1}$), and positively related to firm age and S&P 500 membership. Coefficient estimates on *MVE* confirm that small stocks outperformed large stocks during our sample period.

Since our initial regression specification only provides inference for the subsequent performance of stocks following extreme herding episodes, we amend the original regression specification (7) to account for trading intensity. Specifically, we replace the *IntenseBuy* dummy variable with the interaction term *Buy* × |*Net Trading*$_{k,t}$|, where *Buy* is a dummy variable set to 1 if the herd is buying and |*Net Trading*$_{k,t}$| is the absolute value of the weekly institutional trading imbalance. Similarly, we replace the *IntenseSell* dummy variable with the interaction term *Sell* × |*Net Trading*$_{k,t}$|, where *Sell* is a dummy variable set to 1 if the herd is selling and |*Net Trading*$_{k,t}$| is the absolute value of share imbalance. We present results in Panel B of Table 9. Results are consistent with those in our portfolio analysis. The positive coefficient on the buy herding interaction term indicates that return continuation is greater for more intense buy herds, while the positive coefficient on the sell herding interaction term indicates that return reversals are larger for more intense sell herds. Overall, we have shown robust evidence of return reversal after intense institutional sell herds and return continuation following intense institutional buy herds.

D. Discussion on the Buy/Sell Asymmetry

How do we explain the buy/sell asymmetry in post-herding stock returns? We offer three potential explanations. The first potential explanation is based on Chan and Lakonishok (1993). When institutional investors purchase securities, their choice of which security to buy is likely to be unconstrained. As such, the decision to buy a particular security, out of the numerous possibilities that exist, is likely to convey positive firm-specific information. Alternatively, an institutional investor holds a finite number of securities in his or her portfolio, and when short sales are constrained, faces a limited number of alternatives when deciding to sell. As a result, there are many reasons why institutional sales (e.g. liquidity motivated sales) may not necessarily convey negative firm-specific information.

Our second potential explanation is that institutional sell herds might be more strongly influenced by behavioral factors. There is now ample evidence that emotions or behavioral biases affect investors' decision-making processes (see, e.g., Odean (1998) and Barber and Odean (2007)). Two sentiments appear to have the most lasting impact: fear and greed. Hooke (1999) argues that, "Out of the two emotions, fear is by far the stronger, as evidenced by stock prices, which fall faster than they go up. Afraid of losing money, people demonstrate a classic herd psychology on hearing bad news, and rush to sell a stock before the next investor." (p.7) If institutional sell herds are more strongly influenced by emotions, which is unrelated to firm-specific information, then we would expect to find strong reversals after intense sells.

Our final possible explanation is related to liquidity. As also argued by Chan and Lakonishok (1993), it could be that counterparties are willing to accommodate institutional sales by purchasing shares in exchange for short-term price concessions, but are reluctant to accommodate institutional purchases which may involve taking short positions. Due to the asymmetric relationship of liquidity provision, institutional purchases would be less likely to include temporary price concessions. This explanation is consistent with Campbell, Ramadorai, and Schwartz (2007) who suggest that institutions are particularly likely to demand liquidity when they sell stocks.

The explanations offered above are not mutually exclusive, and may all contribute to the return asymmetry that we document. A complete investigation into the underlying economic reasons for the return asymmetry following institutional short-term buy herds and sell herds is beyond the scope of our current paper.

5. Conclusions

The concentration of institutional ownership and trading activity in equity markets raises important questions concerning the impact of institutional trading on securities prices. Anecdotal evidence suggests that institutions herd together over short time intervals, and that such trading patterns have potential implications for the efficiency of equity prices.

Using the trades of 776 U.S. institutional investors during the period from 1999 to 2004, we examine the existence and consequences of institutional herding at a weekly frequency. Our results indicate robust evidence of short-term institutional herding using both the Lakonishok, Shleifer, and Vishny (1992) herding measure and the Sias (2004) measure. In fact, the herding levels that we document are higher than those found in previous studies using quarterly data.

More importantly, we find that short-term institutional herds have significant implications for the efficiency of security prices. The portfolio of stocks *intensely sold* by institutional herds outperforms the portfolio of stocks *lightly sold* by institutional herds by an average of 0.36% per week during the subsequent four week period. These return reversals are consistent with the popular press view of institutional herds driving asset prices beyond fundamental values. When investigating the subsequent performance of stocks following institutional buy herds we find an asymmetric price response. Specifically, the portfolio of stocks *intensely bought* by institutional herds outperforms the portfolio of stocks *lightly bought* by institutional herds by an average of 0.16% per week during the subsequent four week period. Return continuations following buy herds are consistent with such herds impounding new information into security prices.

Our results differ from the majority of previous studies investigating institutional herding with quarterly or annual data. These studies of "long-term" herding (Nofsinger and Sias (1999);

Wermers (1999); Sias (2004)) generally find that institutional herding is information-based and helps speed up the price adjustment process. Our results are consistent with the hypothesis that institutional buy herds tend to be information-based whereas institutional sell herds tend to be driven by liquidity needs or by other behavioral reasons.

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Figure 1
Cumulative Abnormal Returns of Institutional Trading Portfolios

Figure 1 presents cumulative abnormal returns of institutional trading portfolios over the weeks -4 through 12. The sample period is from 1999 to 2004, and institutional trading data are from the Abel Noser Corporation. We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. We obtain shares outstanding and stock return from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). Each week, we divide all stocks that institutions are net buyers into five buy quintiles, and divide all stocks that institutions are net sellers into five sell quintiles, based on the aggregate institutional trading (scaled by total shares outstanding) on the stock during the week. The intense buy portfolio is the quintile with the most institutional buying. The intense sell portfolio is the quintile with the most institutional selling. We form equal-weighted portfolios and hold these portfolios for twelve weeks. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample.

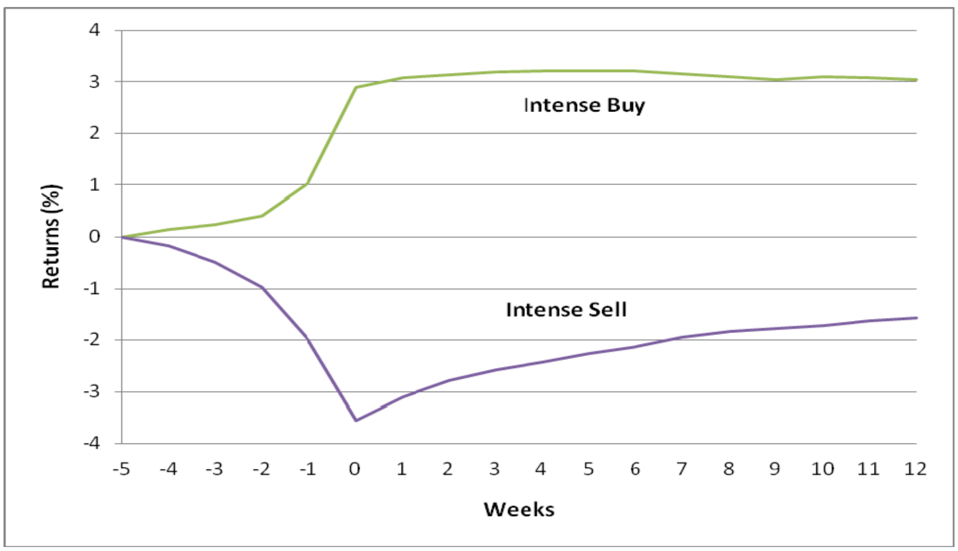

Table 1
Descriptive Statistics for Abel Noser Institutional Trading Data and Stock Characteristics

Table 1 presents descriptive statistics for the Abel Noser institutional trading data and stock characteristics. The trades in the sample are placed by 776 different institutional clients of Abel Noser during the time period from January 1, 1999 to December 31, 2004. We obtain share price, total shares outstanding, return, trading volume, and whether a firm belongs to the S&P 500 index from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). We obtain book value of equity from Compustat. Variables in Panel B are at weekly frequency, measured from Wednesday to Wednesday. Firm age is the number of months since the stock first appears in the CRSP. Return volatility is the average absolute daily stock return within each week. Panel B reports the *time-series* mean, median, standard deviation, maximum, and minimum of weekly *cross-sectional averages*.

Panel A: Abel Noser Institutional Trading Data

	1999	2000	2001	2002	2003	2004
Total Number of Institutions	382	376	404	430	405	406
Total Number of Stocks	6,150	5,906	5,082	4,692	4,736	4,927
Total Number of Trade Executions (millions)	5.64	7.56	9.05	12.32	12.35	21.43
Total Share Volume (billion)	50.69	73.44	100.99	135.04	112.30	155.92
Total Dollar Volume ($trillion)	2.25	3.20	3.06	3.23	2.76	4.46
Mean #Institutions Trading Each Stock Per Week	7.11	8.41	9.68	11.09	11.07	11.67
Median #Institutions Trading Each Stock Per Week	4.00	4.00	5.00	6.00	7.00	8.00
Mean Share Volume Per Trade Execution	8,988	9,714	11,159	10,961	9,093	7,276
Median Share Volume Per Trade Execution	1,700	1,500	1,400	1,300	1,050	700
Mean Dollar Volume Per Trade Execution	398,803	423,726	337,633	262,359	223,126	208,027
Median Dollar Volume Per Trade Execution	60,030	54,970	39,200	30,300	27,297	20,568

Panel B: Stock Characteristics

	Mean	Median	Std. Dev.	Maximum	Minimum
Market Capitalization ($billion)	4.69	4.57	0.73	6.70	3.42
Share Price ($)	54.36	54.19	2.54	61.66	47.87
Return (%)	0.39	0.76	3.15	10.05	-10.66
Firm Age (months)	200.78	201.03	10.01	222.06	174.89
Return Volatility (%)	2.56	2.43	0.76	5.85	1.27
Turnover (%)	4.40	4.43	0.76	6.68	2.06
Book-to-Market Ratio	0.50	0.49	0.06	0.64	0.28
S&P 500 Dummy	0.18	0.18	0.02	0.24	0.14

Table 2
Institutional Herding: The Lakonishok, Shleifer, and Vishny (LSV 1992) Measure

Table 2 presents descriptive statistics for the LSV herding measure. The sample period is from 1999 to 2004. Institutional trading data are from the Abel Noser Corporation. We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. We obtain share price and total shares outstanding from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). Panel A calculates the LSV measure for stocks when at least 2,5,10, 25, or 50 institutions trade in a given week. Panel B reports the LSV measure by firm-size quintile. The LSV Herding measure is expressed in percent. The numbers in parentheses are *p*-values.

Panel A: By Number of Institutions Trading

≥ 2	≥ 5	≥ 10	≥ 25	≥ 50	≥ 50 – ≥ 2
4.78	4.95	5.38	6.52	8.13	3.35
(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)

Panel B: By Firm Size

Q1 (small)	Q2	Q3	Q4	Q5 (large)	Q5 – Q1
6.96	4.18	3.84	3.86	4.98	-1.99
(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)

Table 3
Institutional Herding: The Sias (2004) Measure

Table 3 examines institutional herding using the Sias (2004) measure. The sample period is from 1999 to 2004, and institutional trading data are from the Abel Noser Corporation. We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). For each security and week we calculate the faction of institutional buyers (RawΔ_t), and standardize the variable to have zero mean and unit variance. Using a Fama-MacBeth approach, we estimate a cross-sectional regression for each week and report the time-series average of regression coefficients in the first column. The second and third columns report the partitioned slope coefficient that results from institutions following their own trades and the fraction that results from institutions following the trades of other institutions. Panel B, C, D, and E report time-series coefficient averages and partitioned slope coefficients for the sample of stock week observations with at least 5, 10, 20 or 50 institutional traders. Numbers in parentheses are corresponding *t*-statistics and are computed using the time-series standard error of weekly coefficients.

	Partitioned Slope Coefficient		
Average Coefficient (β)	Institutions Following Their Own Trades	Institutions Following Others' Trades	Average R^2
Panel A: Securities with ≥ 2 Institutional Traders			
0.404	0.171	0.234	16.79%
(129.51)	(90.73)	(87.41)	
Panel B: Securities with ≥ 5 Institutional Traders			
0.374	0.166	0.208	15.40%
(124.17)	(102.35)	(66.36)	
Panel C: Securities with ≥ 10 Institutional Traders			
0.385	0.133	0.251	16.03%
(106.66)	(108.03)	(64.63)	
Panel D: Securities with ≥ 20 Institutional Traders			
0.439	0.092	0.347	19.73%
(77.54)	(88.00)	(59.48)	
Panel E: Securities with ≥ 50 Institutional Traders			
0.563	0.051	0.512	30.18%
(57.78)	(63.54)	(52.73)	

Table 4
Prior and Contemporaneous Returns of Institutional Herding Portfolios

Table 4 presents prior and contemporaneous abnormal performance (in percent) for portfolios of stocks sorted by institutional herding. The sample period is from 1999 to 2004, and institutional trading data are from the Abel Noser Corporation. We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. We obtain shares outstanding and stock return from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). Each week, we divide all stocks that institutions are net buyers into five buy quintiles, and divide all stocks that institutions are net sellers into five sell quintiles, based on the aggregate institutional trading (scaled by total shares outstanding) on the stock during the week. The intense buy portfolio is the quintile with the most institutional buying. The intense sell portfolio is the quintile with the most institutional selling. The light buy portfolio is the quintile with the least institutional buying. The light sell portfolio is the quintile with the least institutional selling. We form equal-weighted portfolios. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample. Numbers in parentheses are Newey-West *t*-statistics.

	Weeks				
Institutional Herding Portfolios	-4	-3	-2	-1	0
1 – Intense Sell	-0.17	-0.32	-0.49	-1.03	-1.54
2	-0.05	-0.08	-006	-0.43	-1.09
3	-0.00	-0.07	-0.09	-0.32	-0.80
4	-0.01	0.02	-0.10	-0.21	-0.59
5 – Light Sell	-0.11	-0.07	-0.05	-0.07	-0.37
6 – Light Buy	0.05	0.05	0.07	0.03	-0.07
7	0.03	0.08	0.04	0.18	0.25
8	0.09	0.06	0.12	0.28	0.58
9	0.13	0.19	0.14	0.44	1.11
10 – Intense Buy	0.15	0.09	0.16	0.64	1.85
Intense Sell – Light Sell	-0.05	-0.26	-0.43	-0.96	-1.18
	(-0.67)	(-3.27)	(-5.17)	(-11.05)	(-11.09)
Intense Buy – Light Buy	0.11	0.04	0.10	0.61	1.92
	(1.30)	(0.51)	(1.08)	(6.00)	(17.58)
Intense Buy – Intense Sell	0.31	0.42	0.65	1.66	3.39
	(5.11)	(6.50)	(9.92)	(20.80)	(39.78)

Table 5
Institutional Herding and Subsequent Stock Performance

Table 5 presents subsequent abnormal performance (in percent) for portfolios of stocks sorted by institutional herding. The sample period is from 1999 to 2004, and institutional trading data are from the Abel Noser Corporation. We obtain share price, shares outstanding and stock return from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. Each week, we divide all stocks that institutions are net buyers into five buy quintiles, and divide all stocks that institutions are net sellers into five sell quintiles, based on the aggregate institutional trading (scaled by total shares outstanding) on the stock during the week. The intense buy portfolio is the quintile with the most institutional buying. The intense sell portfolio is the quintile with the most institutional selling. The light buy portfolio is the quintile with the least institutional buying. The light sell portfolio is the quintile with the least institutional selling. We form equal-weighted portfolios and hold these portfolios for four weeks. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample. We report average weekly abnormal portfolio returns. Numbers in parentheses are Newey-West *t*-statistics.

	Holding Periods (#weeks)			
Institutional Herding Portfolios	1	2	3	4
1 – Intense Sell	0.39	0.35	0.30	0.25
2	0.00	0.01	0.02	0.02
3	-0.07	-0.08	-0.05	-0.04
4	-0.16	-0.12	-0.06	-0.06
5 – Light Sell	-0.19	-0.16	-0.11	-0.11
6 – Light Buy	-0.15	-0.10	-0.09	-0.10
7	-0.02	-0.02	-0.02	-0.03
8	-0.00	-0.01	-0.01	-0.02
9	0.04	0.04	0.03	0.00
10 – Intense Buy	0.15	0.09	0.08	0.06
Intense Sell – Light Sell	0.58	0.51	0.42	0.36
	(7.29)	(7.65)	(6.80)	(5.92)
Intense Buy – Light Buy	0.29	0.19	0.17	0.16
	(3.43)	(2.70)	(2.47)	(2.24)
Intense Buy – Intense Sell	-0.25	-0.25	-0.22	-0.20
	(-3.62)	(-4.53)	(4.03)	(-3.62)

Table 6
Institutional Herding and Subsequent Abnormal Stock Performance – By Firm Size

Table 6 presents subsequent abnormal performance (in percent) for portfolios of stocks sorted by size quintiles and institutional herding. The sample period is from 1999 to 2004, and institutional trading data are from the Abel Noser Corporation. We obtain share price, shares outstanding and stock return from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. Each week, we first divide all stocks into quintiles based on size. Then for each size quintile we divide all stocks that institutions are net buyers into five buy quintiles, and divide all stocks that institutions are net sellers into five sell quintiles, based on the aggregate institutional trading (scaled by total shares outstanding) on the stock during the week. The intense buy portfolio is the quintile with the most institutional buying. The intense sell portfolio is the quintile with the most institutional selling. The light buy portfolio is the quintile with the least institutional buying. The light sell portfolio is the quintile with the least institutional selling. We form equal-weighted portfolios and hold these portfolios for four weeks. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample. We report average weekly abnormal portfolio returns. Numbers in parentheses are Newey-West *t*-statistics.

Panel A: Intense Sell – Light Sell

	Holding Periods (#weeks)			
Firm Size Quintile	1	2	3	4
1 – Small	1.14 (6.88)	1.04 (8.67)	0.89 (8.92)	0.76 (7.87)
2	0.74 (6.27)	0.58 (6.29)	0.46 (5.56)	0.36 (4.47)
3	0.34 (2.85)	0.37 (4.25)	0.28 (3.72)	0.25 (3.26)
4	0.27 (2.31)	0.19 (2.03)	0.17 (2.01)	0.14 (1.73)
5 – Large	0.24 (2.14)	0.17 (2.04)	0.13 (1.78)	0.16 (2.18)

Panel B: Intense Buy – Light Buy

	Holding Periods (#weeks)			
Firm Size Quintile	1	2	3	4
1 – Small	0.44 (3.44)	0.27 (2.89)	0.27 (3.24)	0.25 (3.19)
2	0.34 (2.97)	0.24 (2.71)	0.21 (2.30)	0.22 (2.56)
3	0.22 (1.75)	0.11 (1.14)	0.09 (0.96)	0.07 (0.77)
4	0.24 (1.96)	0.19 (1.93)	0.17 (1.78)	0.15 (1.59)
5 – Large	0.20 (1.61)	0.11 (1.00)	0.06 (0.63)	0.05 (0.53)

Panel C: Intense Buy – Intense Sell

	Holding Periods (#weeks)			
Firm Size Quintile	1	2	3	4
1 – Small	-0.60 (-3.93)	-0.59 (-4.90)	-0.52 (4.67)	-0.46 (-4.43)
2	-0.27 (-2.08)	-0.23 (-2.42)	-0.21 (-2.53)	-0.16 (-2.10)
3	-0.09 (-0.91)	-0.16 (-2.22)	-0.15 (-2.30)	-0.13 (-2.12)
4	-0.10 (-0.95)	-0.07 (-0.81)	-0.05 (-0.65)	-0.05 (-0.69)
5 – Large	-0.07 (-0.67)	-0.12 (-1.38)	-0.10 (-1.31)	-0.12 (-1.67)

Table 7
Institutional Herding and Subsequent Stock Performance – Pension Plan Sponsors

Table 7 presents subsequent abnormal performance (in percent) for portfolios of stocks sorted by institutional herding of pension plan sponsors only. The sample period is from 1999 to 2004, and institutional trading data are from the Abel Noser Corporation. We obtain share price, shares outstanding and stock return from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. Each week, we divide all stocks that institutions are net buyers into five buy quintiles, and divide all stocks that institutions are net sellers into five sell quintiles, based on the aggregate institutional trading (scaled by total shares outstanding) on the stock during the week. The intense buy portfolio is the quintile with the most institutional buying. The intense sell portfolio is the quintile with the most institutional selling. The light buy portfolio is the quintile with the least institutional buying. The light sell portfolio is the quintile with the least institutional selling. We form equal-weighted portfolios and hold these portfolios for four weeks. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample. We report average weekly abnormal portfolio returns. Numbers in parentheses are Newey-West *t*-statistics.

	Holding Periods (#weeks)			
Institutional Herding Portfolios	1	2	3	4
1 – Intense Sell	0.45	0.32	0.27	0.23
2	0.06	0.07	0.06	0.06
3	-0.07	-0.07	-0.03	-0.02
4	-0.16	-0.13	-0.10	-0.08
5 – Light Sell	-0.22	-0.19	-0.12	-0.11
6 – Light Buy	-0.14	-0.11	-0.10	-0.10
7	-0.04	-0.02	-0.01	-0.03
8	0.05	0.01	-0.01	-0.04
9	0.04	0.03	0.00	-0.02
10 – Intense Buy	0.06	0.09	0.06	0.03
Intense Sell – Light Sell	0.66	0.51	0.40	0.34
	(8.20)	(7.51)	(6.05)	(4.96)
Intense Buy – Light Buy	0.20	0.20	0.16	0.13
	(2.49)	(3.10)	(2.46)	(1.98)
Intense Buy – Intense Sell	-0.38	-0.23	-0.21	-0.19
	(-5.37)	(-4.62)	(-4.34)	(-3.87)

Table 8
Institutional Herding and Subsequent Stock Performance –Multi-Factor Alphas

Table 8 presents subsequent abnormal performance (in percent) for portfolios of stocks sorted by institutional herding. The sample period is from 1999 to 2004, and institutional trading data are from the Abel Noser Corporation. We obtain share price, shares outstanding and stock return from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). We obtain daily Fama and French (1993) factors and the momentum factor from Kenneth French's Website. We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. Each week, we divide all stocks that institutions are net buyers into five buy quintiles, and divide all stocks that institutions are net sellers into five sell quintiles, based on the aggregate institutional trading (scaled by total shares outstanding) on the stock during the week. The intense buy portfolio is the quintile with the most institutional buying. The intense sell portfolio is the quintile with the most institutional selling. The light buy portfolio is the quintile with the least institutional buying. The light sell portfolio is the quintile with the least institutional selling. We form equal-weighted portfolios and hold these portfolios for four weeks. Average weekly portfolio returns are reported in Panel A (Fama-French three-factor alpha) and Panel B (Carhart (1997) four-factor alpha). Numbers in parentheses are Newey-West *t*-statistics.

Panel A: Fama-French 3-factor Alpha

	Holding Periods (#weeks)			
	1	2	3	4
Intense Sell – Light Sell	0.56	0.49	0.41	0.34
	(8.65)	(8.60)	(7.41)	(6.50)
Intense Buy – Light Buy	0.27	0.17	0.16	0.15
	(4.21)	(2.97)	(2.90)	(2.47)
Intense Buy – Intense Sell	-0.26	-0.26	-0.22	-0.19
	(-3.75)	(-4.64)	(-4.31)	(-3.74)

Panel B: Carhart 4-factor Alpha

	Holding Periods (#weeks)			
	1	2	3	4
Intense Sell – Light Sell	0.58	0.50	0.42	0.35
	(8.97)	(9.02)	(7.71)	(6.64)
Intense Buy – Light Buy	0.26	0.17	0.16	0.15
	(4.04)	(3.04)	(2.91)	(2.52)
Intense Buy – Intense Sell	-0.29	-0.27	-0.24	-0.19
	(-4.24)	(-5.02)	(-4.75)	(-3.88)

Table 9
Institutional Herding and Subsequent Stock Performance – Cross-Sectional Regressions

Table 9 presents results of regressions of future stock returns on institutional herding. The sample period is from 1999 to 2004. Institutional trading data are from the Abel Noser Corporation. We aggregate institutional trading data to weekly frequency, measured from Wednesday to Wednesday. We obtain share price, total shares outstanding, return, trading volume, and whether a firm belongs to the S&P 500 index from the CRSP stock database. Our sample includes only common stocks (those with a sharecode of 10 or 11 in CRSP). We obtain book value of equity from Compustat. Each week, we divide all stocks that institutions are net buyers into five buy quintiles, and divide all stocks that institutions are net sellers into five sell quintiles, based on the aggregate institutional trading (scaled by total shares outstanding) on the stock during the week. The intense buy portfolio is the quintile with the most institutional buying. The intense sell portfolio is the quintile with the most institutional selling. The dependent variables are one, two, three, and four-week-ahead stock returns. We run each regression each week and report the time-series average regression coefficients. We compute *t*-statistics (in parentheses) for each mean regression coefficient using the Fama and MacBeth (1973) approach.

Panel A: Intense Buy and Intense Sell Dummies

	Dependent Variable							
	$RET_{t,t+1}$		$RET_{t,t+2}$		$RET_{t,t+3}$		$RET_{t,t+4}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.900	2.026	3.572	3.878	4.928	5.356	6.330	6.818
	(4.34)	(4.95)	(5.15)	(6.47)	(5.44)	(6.83)	(5.79)	(7.10)
Intense Buy Dummy	**0.161**	**0.191**	0.149	**0.215**	0.159	**0.273**	0.160	**0.307**
	(2.84)	(4.44)	(1.82)	(3.51)	(1.54)	(3.70)	(1.37)	(3.83)
Intense Sell Dummy	**0.344**	**0.338**	**0.588**	**0.591**	**0.771**	**0.800**	**0.872**	**0.907**
	(6.09)	(7.35)	(7.61)	(9.63)	(7.94)	(10.54)	(7.76)	(10.41)
$RET_{t-5, t-1}$	-0.004	-0.008	-0.004	-0.012	-0.003	-0.012	-0.003	-0.014
	(-0.87)	(-2.64)	(-0.72)	(-2.82)	(-0.35)	(-2.40)	(-0.38)	(-2.31)
$LogMarketCap_{t-1}$	-0.117	-0.136	-0.221	-0.263	-0.303	-0.364	-0.388	-0.461
	(-4.34)	(-4.41)	(-5.43)	(-6.38)	(-5.77)	(-7.22)	(-6.15)	(-7.71)
$LogAge_{t-1}$		0.060		0.121		0.189		0.256
		(2.10)		(2.93)		(3.61)		(4.18)
$LogVolatility_{t-5, t-1}$		-0.016		-0.044		-0.080		-0.113
		(-0.42)		(-0.78)		(-1.14)		(-1.37)
$LogPrice_{t-1}$		-0.060		-0.101		-0.144		-0.194
		(-0.79)		(-0.86)		(-0.96)		(-1.07)
$BMDecile_{t-1}$		0.009		0.017		0.027		0.034
		(0.82)		(1.07)		(1.28)		(1.35)
$SP500_{t-1}$		0.155		0.294		0.381		0.452
		(2.45)		(3.63)		(4.11)		(4.25)
Average R-Squared	2.69%	7.27%	3.16%	8.62%	3.34%	9.27%	3.49%	9.86%

Panel B: Trading Intensity

	Dependent Variable							
	$RET_{t,t+1}$		$RET_{t,t+2}$		$RET_{t,t+3}$		$RET_{t,t+4}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.898	2.025	3.547	3.863	4.888	5.324	6.262	6.758
	(4.34)	(4.95)	(5.11)	(6.44)	(5.40)	(6.80)	(5.74)	(7.06)
Buy ×| $NetTrading_{t-1,t}$ |	**0.152**	**0.161**	**0.206**	**0.208**	**0.242**	**0.269**	**0.298**	**0.352**
	(3.79)	(4.39)	(3.54)	(4.32)	(3.18)	(4.36)	(3.28)	(5.05)
Sell ×| $NetTrading_{t-1,t}$ |	**0.177**	**0.200**	**0.356**	**0.379**	**0.507**	**0.535**	**0.617**	**0.641**
	(4.32)	(5.77)	(6.38)	(8.18)	(7.28)	(8.78)	(7.62)	(9.14)
$RET_{t-5, t-1}$	-0.004	-0.008	-0.004	-0.012	-0.002	-0.012	-0.003	-0.013
	(-0.85)	(-2.60)	(-0.71)	(-2.79)	(-0.34)	(-2.38)	(-0.35)	(-2.26)
$LogMarketCap_{t-1}$	-0.117	-0.136	-0.220	-0.263	-0.301	-0.364	-0.385	-0.460
	(-4.33)	(-4.42)	(-5.41)	(-6.38)	(-5.74)	(-7.20)	(-6.12)	(-7.67)
$LogAge_{t-1}$		0.059		0.121		0.190		0.258
		(2.08)		(2.92)		(3.63)		(4.21)
$LogVolatility_{t-5, t-1}$		-0.015		-0.043		-0.080		-0.114
		(-0.40)		(-0.76)		(-1.13)		(-1.38)
$LogPrice_{t-1}$		-0.058		-0.098		-0.141		-0.193
		(-0.76)		(-0.84)		(-0.94)		(-1.06)
$BMDecile_{t-1}$		0.008		0.017		0.026		0.035
		(0.78)		(1.07)		(1.27)		(1.37)
$SP500_{t-1}$		0.156		0.296		0.379		0.451
		(2.47)		(3.65)		(4.09)		(4.25)
Average R-Squared	2.70%	7.30%	3.17%	8.65%	3.35%	9.31%	3.52%	9.91%