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Institutional Herding and Future Stock Returns*

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Abstract

When the trading of institutional investors is imbalanced between buys and sells, how are stock prices affected? The extant literature on such herding by institutions, represented by Wermers (1999) and Sias (2004), concludes that herding promotes price discovery and helps adjust prices to their intrinsic levels. That is, they find herding to correctly predict stock returns in the coming months. In contrast, two to three years after the herding, we find that stocks with buy herds realize negative abnormal returns. This longer run reversal in returns is robust across subperiods and performance metrics and impedes the interpretation of herding as solely promoting price discovery. In addition, we find that non-13F investors, roughly labeled individual investors, suffer these longer run reversals in returns. The performances of the herding and nonherding institutions are less clear. On the sell side, however, herding does not explain future abnormal returns.

Institutional investors are increasingly larger players in equity markets. Their ownership of U.S. stocks has more than doubled in the past twenty years to over 60% of the total market value, and their trading volume accounts for over 90% of the total dollar volume.[1] Consequently, there is much interest in the trading behaviors of institutional investors and their effects on stock prices. Beginning at least with Kraus and Stoll (1972a) and more recently with Lakonishok, Shleifer, and Vishny (1992), economists have recognized the possibility that institutions relying on similar information and facing similar incentives might trade in the same direction. Hirshleifer and Teoh (2003) and Brunnermeier (2001) provide a detailed and rich review of the large literature on herding, providing overviews of theories as well as the evidence from financial markets. In short, institutions might trade in the same direction for at least four reasons. One, they observe similar information. Two, they favor stocks with certain characteristics, such as "prudent," liquid, or better-known stocks. Three, money managers concerned for their reputations choose to mimic the trades of other managers. Four, managers infer stock-valuation signals from others managers' trades.[2]

These motivations for institutions to herd in their trades can result in varying effects on stock prices. On one hand, as sophisticated and better-informed investors, institutions might push prices *toward* their intrinsic values when they herd in their trading. On the other hand, institutions might drive prices *away* from intrinsic levels if their herding is based on characteristic preferences or managerial reputation.

Examining future stock returns offers a means of determining whether herding pushes prices toward or away from intrinsic price levels. Wermers (1999) in his study of mutual funds and Sias (2004) in his study of all institutions provide the most recent analyses on this issue. Each measures herding as an imbalance of institutions that are net buyers or net sellers over a given quarter, and each finds that the buy/sell imbalance of institutional trades correctly anticipates the next several months of stock

[1]Institutional ownership is estimated from 13F filings provided by Thomson Financial. The trading volume estimates come from Kaniel, Saar, and Titman (2006) who examine all orders executed on the NYSE from 2000 to 2003 for all listed common U.S. stocks.

[2]Sias (2004) also provides a useful reference for studies identifying these motives to herd.

returns. They conclude that herds of institutional trades tend to reduce mispricings, thereby aiding price discovery.

However, a longer run analysis is warranted. If a mispricing in fact does stem from the herding, we learn from many studies of stock returns that presumed correctional reversals in prices tend to occur at horizons longer than one year. For example, Jegadeesh and Titman (1993) and many others find a second-year reversal in returns to follow the initial momentum in returns. Also, we should note that both Wermers (1999) and Sias (2004) find evidence of a return reversal occurring at the end of the year following the herd, granted this end-of-year reversal is small relative to the return continuations earlier in the year.[3]

In this study, we examine the relations between longer run stock returns and institutional herding from 1980 to 2005. While we confirm earlier findings that a preponderance of net buyers (or net sellers) correctly predicts shorter run returns, we find a robust return reversal which begins in the fourth quarter after the herding and persists throughout years two and three. Our findings suggest that institutional herding does result in stock prices that reliably deviate from intrinsic levels, altering the extant view of herding as solely benefiting price discovery.

Furthermore, the longer run return reversal is concentrated on the buy side, with stocks in the top decile of herding experiencing about a negative 4% return over years two and three, adjusted for size, book-to-market equity, and momentum effects. Herding on the sell side has no relation to future returns across our full sample period, though it does predict poor performance in the first half of our sample, similar to Wermers' (1999) sample period and results. In contrast, the return reversals driven by the buy herds are strongly evident in both halves of our sample period. We offer conjectures for why the concentration of the return reversal is on the buy side in the conclusion of the paper.

[3]See Table VI of Wermers (1999) and Table 5 of Sias (2004).

Given that the longer run reversal finding on the buy side is the novel result of this study, we focus our main attention on this reversal and its robustness.[4] This longer run return reversal is evident in portfolios of stocks with extreme herds, in cross-sectional regressions identifying a sensitivity of future returns to variations in herding, in both small and large stocks, and across a variety of performance metrics.[5]

After linking the return reversals to buy herds, we turn our attention to the herding institutions and their trading acumen regarding the stocks into which they herd. Do these institutions suffer the impending return reversals, or do they sell beforehand? To address this, we evaluate the performances of portfolios formed by aggregating the stock holdings of the institutions comprising a herd. These portfolios are tracked for three years following the herd, and stock weights are updated quarterly using the holdings data. We find mixed evidence of abnormal returns in the herding institutions' trading of the buy-herd stocks, and can make no clear conclusions. Similarly, the findings for the other, non-herding institutions are also mixed. In contrast, the third type of investor that we examine, the "individual" investors, defined as the complement of the 13F holdings, bear robust reversals in stock returns. Furthermore, we find that individual investors, after the herding quarter, increase their positions in stocks for which future abnormal returns are negative. These findings for individual investors are evident in both halves of our sample period. In short, institutional herding is ultimately hurting at least one group of investors – individual investors.

Overall, our finding of longer run reversals in stock returns following institutional herding transforms our understanding of herding from an aid in the process of price

[4]Brown, Wei, and Wermers (2007) find that the herding of mutual fund trades in recent years predicts shorter run (year one) return reversals. They highlight the differences in shorter run returns between the last fifteen years and prior periods, consistent with differences we detect using 13F data. Our main focus however is on longer run returns, years two and three. We find that reversals in these longer horizons have existed since 1980, as far back as we can look. Also, Coval and Stafford (2007) find return reversals following herds of mutual fund trades driven by extreme fund flows. By examining herds of fire sales and purchases, which are rare events, they cannot speak to any overall, unconditional effects of herding, which is our focus.

[5]We also examine changes in the level of aggregate institutional ownership (ΔIO), which is positively correlated with the proportion of trading institutions that are net buyers, and find that it also predicts long run return reversal. However, the proportion of buyers dominates ΔIO as a predictor of long run reversal. That is, the imbalance across the numbers of buyers and sellers is more important than the imbalance across the sizes of the buys and sells.

discovery to a presumed trigger of mispricings which require the future reversal in returns. Future research with higher frequency trade data can perhaps shed more light on the dynamics of the trading between institutional and individual investors in these stocks, including more examinations of whether institutions profit from their herding.

In addition, our results indicate that future researchers of institutional herding must carefully control for returns contemporaneous and prior to the herding quarter. We find that the failure to control for these returns significantly affects standard measures of future abnormal returns of stocks with herds, potentially confounding a herding effect on stock prices with a lagged-return effect.

In section 1, we present the data and methodology. Section 2 details our examinations of the relations between herding and future stock returns. Section 3 discusses motives for herding and examines the trading performances of investors in the buy-herd stocks. We conclude in section 4.

1. Data and Methodology

The data on institutional stock holdings are obtained from Thomson Financial and are gathered from 13F filings of institutional investors from 1980 to 2005. We gather stock price, shares outstanding, and return data from CRSP and book value of equity from Compustat. After merging these data sources and cleaning the holdings data, we have a sample of 4,115 institutions. Details of our handling of the 13F data are given in the appendix.

1.1. Herding Measure

Our measure of herding is based on Lakonishok, Shleifer, and Vishny's (1992) and is commonly used in the literature. For each institution and each stock in quarter t, we first determine the change in the number of shares held from quarter $t-1$ to quarter t, adjusted for stock splits. Herding by institutions for each stock in quarter t is then defined as follows.

$$HERD_t = \frac{\text{number of net buyers}}{\text{number of net buyers } + \text{ number of net sellers}} \tag{1}$$

This variable measures the imbalance of institutional trading between buys and sells. Note that we are not concerned with whether the herding is greater than that which might have occurred by chance, as Lakonishok, Shleifer, and Vishny (1992) and Kraus and Stoll (1972a) are. Our interest is simply to examine the effects of institutional trades on stock prices when these trades cluster together.

For all of our tabulated results, we require a stock to have at least 10 institutional traders in quarter t and institutional ownership less than or equal to 100% of the shares outstanding. Varying the filter on the number of traders from 1 to 20 has little effect on our overall findings. Inspection of the data reveals that imposing a maximum of 100% institutional ownership results in the removal of extreme observations that are surely data errors. Also, we consider a second measure of herding using the number of shares bought and sold, instead of the number of buyers and sellers, and our main findings remain.[6]

1.2. Abnormal Returns

Our tests examine the relation between herding and future abnormal returns. The measure of abnormal returns that we employ accounts for size, book-to-market equity, and momentum effects. As done by Daniel, Grinblatt, Titman, and Wermers (1997), hereafter "DGTW," and many others, we identify a benchmark portfolio for each stock

[6] We discuss the results using the share-based measure, as well as using the change in the percentage of institutional ownership, in section 2.4. For several reasons we prefer to measure herding based on the numbers of buyers and sellers instead of the numbers of shares bought and sold. First, Jones, Kaul, and Lipson (1994) find that stock price movements are due more to the number of trades than to the size of trades, and Sias, Starks, and Titman (2006) find that the number of institutions holding a stock is more strongly related to returns than is the percentage of institutional ownership. Second, the reputational motive to follow the herd considers the imbalance in the number of institutions buying or selling. And, although less clear, the signal-inference motive would seem to weight the number of traders more than the volume traded since the sizes of managed portfolios can vary greatly. Last, the price impact of a single trader with a given trade size should be lower than that of a number of traders with a collectively similar trade size, as the single trader can strategically work his order over time to reduce price impact.

each quarter. We form these benchmark portfolios each June-end using the following three-way dependent sorting procedure. First, we sort all available stocks from CRSP into five size groups according to their market value of equity at the end of June, with breakpoints based on NYSE stocks only. Then, within each of these size groups, we sort stocks into five groups based on their book-to-market ratios, where the book value of equity is from the fiscal year-end in the calendar year preceding the July formation of the benchmarks and the market value of the equity is from the prior December. Finally, we sort stocks in each size/book-to-market group into quintiles based on their 12-month return ending in May. We calculate the quarterly equally weighted returns for each of the 125 benchmark portfolios in September, December, March, and June. We subtract each specific stock's corresponding benchmark return from the stock's quarterly return to arrive at an abnormal return. We use equally weighted benchmark returns since both our portfolio and regression analyses examine stocks on an equally weighted basis. Using monthly returns instead of quarterly does not alter the main findings.

2. Relations between Herding and Future Abnormal Returns

2.1. Portfolios of Stocks with Extreme Herding

Each quarter we rank all stocks into deciles based on $HERD_t$. The top decile of $HERD_t$ identifies the extreme buy herd, and the bottom decile identifies the extreme sell herd. We calculate abnormal returns for each of these two equally weighted portfolios over various event quarters in calendar time and then obtain standard errors from the resulting time series. When examining multiquarter windows, we first average abnormal portfolio returns across all available event quarters in each calendar quarter. For example, with the event window $[t+5, t+8]$, there are four extreme-buy-herd portfolios as just described which are in event quarters 5, 6, 7, and 8 respectively in a given calendar quarter. To examine the abnormal performances of the extreme-buy-herd stocks over the event window $[t+5, t+8]$, we calculate the mean abnormal return across the four portfolios in that calendar quarter.

Before examining the performances of these portfolios, we briefly describe the extent of the herding we are detecting. We calculate the means of various measures each quarter and report below the mean of these means (and the mean of the medians in parentheses).

	No. of Traders	$HERD_t$	ΔIO_t
Buy Herd	30 (22)	0.75 (0.73)	5.42 (3.15)
Sell Herd	58 (27)	0.32 (0.34)	−3.53 (−1.64)

We see that stocks in the upper decile of $HERD_t$ have a mean number of 30 institutions changing their net holdings of a given stock in a given quarter across our sample period, and a median number of 22. The fraction of buys to total trades is roughly 3 out of 4, and the fraction of institutional ownership of a stock's outstanding shares increases by a mean of 5.42% and a median of 3.15%. The sell-herd stocks in the bottom decile of $HERD_t$ also have a large buy/sell imbalance, with roughly 1 out of 3 trades being buys, and the change in institutional holdings is also large with a mean decrease of −3.53% and a median decrease of −1.64%.

We now turn to examining the performances of these buy-herd and sell-herd stocks. Table 1 reports the mean quarterly abnormal returns over various event-time windows for the stocks with the highest values of $HERD$, the buy-herd stocks, and the lowest value of $HERD$, the sell-herd stocks. Concentrating first on the relation between buy herding and future returns, we see that stocks with extreme buy herds continue to perform well in the first quarter after the herd, with an alpha of 80 basis points per quarter and a t-statistic of 2.45. This brief continuation in returns echoes the findings of Wermers (1999) and Sias (2004). Table 1 also shows that the buy-herd stocks display no abnormal returns in quarters 2 or 3, but in quarter 4, we see a strong negative return of 75 basis points with a t-statistic (in absolute value) greater than 3.0. Wermers (1999) and Sias (2004) also detect a reversal in quarter 4. We will have more to say in the next section about our shorter term findings relative to these prior studies.

The main – and new – finding of Table 1 is the strong longer run reversal in returns displayed in years two and three. The buy-herd stocks have an alpha of negative 59 and negative 42 basis points per quarter, respectively, across year two and year three, with t-statistics greater than 2.2 in each case. The longer run reversals are strong enough to offset any brief continuation in returns following the buy herd. Specifically, the alpha estimate across quarters 1 through 12 is negative 0.30% with a $t-$statistic of 1.86. These longer run reversals following a buy herd are robust across alternative measures of abnormal returns, across subperiods, and across large and small stocks. We discuss each of these considerations in more detail in later sections.

Before moving to the performances of the extreme sell-herd stocks, we should highlight the dramatically large abnormal returns occurring in the two quarters before we measure herding as well as in the formation quarter. Table 1 reports abnormal returns between 6% and 11% per quarter over these horizons. This is not surprising, but it does present an important issue. Much evidence links institutional trading to prior returns. Specifically, Bennett, Sias, and Starks (2003), Chen, Hong, and Stein (2002), and others find that changes in institutional stock holdings are strongly positively related to both current and lagged returns. Furthermore, Wermers (1999) and Sias (2004) find the institutional herding measure we employ here to be positively related to current and past returns as well. Since the DGTW measure of abnormal returns only controls for 12-month returns ending in May, we expect to see large abnormal returns in quarters -2 to 0. Wermers (1999) and Sias (2004) find this as well. However, given that various horizons of shorter term lagged returns are known to each display marginal effects on future returns (see Gutierrez and Kelley (2008)), it is therefore important to control for these lagged-return effects in our examinations of future returns. As Jegadeesh and Titman (1993) and many subsequent studies document, returns over several quarters are persistent for several more quarters but tend to reverse over longer run horizons. Therefore, we need to ensure that the perceived effects of herding on future returns are distinct from the known effects of lagged returns. In subsequent tests we control explicitly for returns in quarters -2 to 0.

Finally, Table 1 also shows that stocks with extreme sell herds display no evidence of abnormal returns in any of the future windows we examine. It is interesting to note that our sell-side results differ from Wermers' (1999) as he finds evidence of return continuation on the sell side of herding. This difference is due to variation across sample periods, as we discuss in the next section.

Note also from Table 1 that the shorter run continuation and the longer run reversal in the returns of the buy-herd stocks makes the return spread between the buy-herd and sell-herd stocks display both of these patterns as well. In other words, herding predicts future reversals in returns unconditionally as well, not only when conditioning on a buy herd.

2.2. Reconciling our Results with Prior Studies

While we examine abnormal returns over a much longer future window than prior studies do, our shorter run results for the extreme sell herds find no relation with future returns from 1980 to 2005. In contrast, Wermers (1999) finds that sell herds predict low future returns from 1975 to 1994 in the four quarters following the sell herd. Since Sias (2004) does not consider buy and sell herds separately, we focus our comparison on Wermers' study, in particular his Table VI. At this point in our study, we have three variations in our test design from that of Wermers. One, we have a different sample period. Two, we use 13F data while Wermers uses mutual fund data. Three, we examine returns adjusted for size, book-to-market equity, and prior twelve-month return effects while Wermers adjusts for only size effects.[7]

[7] The 13F data are holdings data for all institutions (with at least $100 million under management and for positions of least $200,000 or 10,000 shares), whereas the mutual fund data used by Wermers (1999) are only holdings of mutual funds. The 13F data might provide an advantage in a study of herding as the data better reflect overall institutional demand. However, as the 13F data are aggregated over all money managers within a given institution, some information is possibly lost. Other differences between 13F and mutual fund holdings are the timing and frequency of the reporting. 13F reports must be filed each calendar quarter while mutual fund reporting is based on fiscal year ends of each fund and was required only semiannually until 2004.

To ascertain which of the three appears to be the driver of our sell-side finding, we begin by splitting our sample into two halves, 1980 to 1992 and 1993 to 2005, with the early sample including all formation periods through the end of 1992. Table 2 provides the performances of the portfolios of stocks with extreme buy and sell herds, as in Table 1. Panel A gives the early results and Panel B the later. We see in Panel A that the earlier sample period produces results very similar to those of the "heavy buying" and "heavy selling" portfolios in Table VI of Wermers (1999). Both our extreme buy-side and extreme sell-side herding predict short-run continuations in returns. These continuations last only for one quarter on the buy side but several quarters on the sell side, similar to Wermers' results. Also, our buy-side portfolio displays a return reversal in the fourth quarter just as Wermers' does.

The later sample period, given in Panel B, finds no evidence of continuations in returns following neither buy nor sell herds. Importantly, the buy side still displays longer run reversal starting in quarter 4 and continuing through year 3. The sell side, however, now produces a different return pattern as there are large positive point estimates of alphas, for example above 60 basis points per quarter in year two, but no statistical significance. We also examine abnormal returns adjusted for size and book-to-market equity only and for size only. These alphas are similar to those in Table 2. For the sell herd, these alternative measures offer evidence of statistical reversal in the later period. Brown, Wei, and Wermers (2007) find statistical evidence of reversals in returns in the fourth quarter following both buy and sell herding of mutual funds in a similar sample period from 1994 to 2003. The upshot of all this is that the sample period drives the sell-side differences between our findings and those of Wermers (1999).

To see this in perhaps an easier way, the top plot of Figure 1 clearly depicts our findings for the stocks with extreme buy herds. Here we cumulate the abnormal returns quarter by quarter in event time. We can see that the alphas of these stocks are negative in the longer run across the full period as well as the two subperiods. The returns of these buy-herd stocks are persistently negative from quarter 4 to about quarter 12.[8]

[8]We examine performances out to quarter 20 but find no reliably nonzero alphas beyond quarter 12.

The bottom plot of Figure 1 shows our findings for the stocks with extreme sell herds. The early period finds continuations in the returns of the sell-herd stocks, but no longer run reversals. Moreover, the later period finds reversals in returns from quarter 4 to about quarter 11, but these are not statistically significant, as noted in Table 2. Nevertheless, the point estimates from the later period are impressive going from roughly 0% in quarter 3 to a cumulative 4% in quarter 9.

As discussed earlier, prior returns during quarters $-2, -1,$ and 0 can confound the effects of herding on future returns, especially in the more recent years as the abnormal returns from $[t-2, t]$ grow substantially (see Panel B of Table 1). To illustrate this, we form portfolios that are neutral regarding raw returns over the formation quarter, r_t, as well as raw returns over the two quarters prior to formation, $r_{t-2,t-1}$. Each quarter we first sort all stocks into quintiles based on r_t. We then sort each of these five portfolios into five further portfolios based on $r_{t-2,t-1}$. Lastly, we sort each of these 25 portfolios into deciles based on $HERD_t$. Each calendar quarter, we combine all the stocks in the 25 portfolios with the largest values of $HERD_t$ into an equally weighted portfolio to estimate the performances of the extreme buy-herd stocks controlling for both r_t and $r_{t-2,t-1}$. We do the analogous procedure for the extreme sell-herd stocks, the stocks in the lowest deciles of $HERD_t$.

The cumulative abnormal returns controlling for both r_t and $r_{t-2,t-1}$ are plotted in Figure 2 for the extreme buy-herd and sell-herd stocks in the early and late subperiods. First, in the top graph, we can see that controlling for lagged returns has little effect on the buy side, another indication of the robustness of the longer run reversal in returns. Specifically, using calendar-time tests as in Table 2, both the early and late abnormal returns on the buy side display significant reversals across quarters 5 to 8 with t-statistics above 1.98. Second, on the sell side of the herding, we see in the bottom graph that lagged returns account for the disparity across subperiods shown in Figure 1. In fact, using calendar-time tests once again, we find that in the later subperiod across quarters 5 to 8, the alpha on the sell-herd stocks controlling for r_t and $r_{t-2,t-1}$ is

65 basis points per quarter lower than the DGTW alpha in Table 2, with a t-statistic of 2.32. This finding is a caution to current and future researchers of herding and stock returns: Standard procedures to control for the effects of lagged returns may not be sufficient.

In short, the findings of longer run reversal in the returns of stocks with extreme buy herds is robust across sample periods and methods for defining abnormal returns. These reversals strongly contrast with the messages of the shorter-run studies of Wermers (1999) and Sias (2004).

2.3. Cross-Sectional Regressions

2.3.1. Method

We employ cross-sectional regressions to further examine the relation between herding and future abnormal returns. Regressions allow us to succinctly examine the full cross section of stocks, not only those in the extremes of herding, and to precisely control for lagged returns. In the prior section, we discuss the need to control for r_t and $r_{t-2,t-1}$ based on the findings in Table 1. Furthermore, the additional return-neutral portfolio testing, discussed above, offers evidence that failure to control for these return effects can substantially alter estimates of the effect herding has on future returns. The portfolio testing, however, is limited in its ability to account for lagged returns since quintile sorts are used, leaving some variation within the portfolios. Employing r_t and $r_{t-2,t-1}$ in the regressions as controls allows us to fully account for the effects these measures can have on future returns.[9]

Also in the prior section, we see the disparity between the buy herd and sell herd effects on future returns. Specifically, the sell herd has little relation to future returns while the buy herd predicts a strong longer run reversal in returns. We therefore accommodate this asymmetry in our regressions. We define two continuous measures of

[9]Controlling for $r_{t-4,t-1}$ as well does not alter the findings.

herding,

$$BuyHERD_t = \begin{cases} HERD_t & \text{if } HERD_t \geq \overline{HERD_t} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$SellHERD_t = \begin{cases} HERD_t & \text{if } HERD_t < \overline{HERD_t} \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where $\overline{HERD_t}$ is the cross-sectional median of $HERD$ in quarter t. Similar adjustments are commonly used in the literature to define buying and selling herds. Employed as regressors, the two above measures estimate the slopes of the relations between herding and future returns across buy and sell herding respectively.

We estimate the following cross-sectional regression each quarter.

$$AR_{t+k} = a + b_1 BuyHERD_t + b_2 SellHERD_t + b_3 r_t + b_4 r_{[t-2,t-1]} + b_5 DUM_t^{Buy} + \epsilon_t, \quad (4)$$

where AR_{t+k} is the benchmark-adjusted quarterly return for a given stock in quarter $t+k$, with k varying from 1 to 12 quarters in the future, $BuyHERD$ and $SellHERD$ are the measures just defined, r_t is the raw return of the stock in quarter t, $r_{t-2,t-1}$ is the raw return over the two prior quarters, and DUM_t^{Buy} is a dummy variable set to one when $HERD_t \geq \overline{HERD_t}$ and zero otherwise. The respective t-statistics are calculated by dividing the mean of the quarterly time series of each coefficient by its time-series standard error. When we examine multiple-quarter windows of future returns, for example quarters 5 through 8, we pool the time series of coefficients from each single-quarter analysis. That is, to explain abnormal returns in the quarter ending October 1988, we consider four estimates of b_1 corresponding to four separate and rolling regressions, one using the $BuyHERD$ in June of 1987 (5 quarters back), another using $BuyHERD$ in March 1987 (6 quarters back), and so on. We account for any contemporaneous correlations in the coefficient estimates by clustering the standard errors within each calendar quarter. Using the efficient-weighting procedure of Ferson and Harvey (1999) to account for heteroskedasticity or using monthly abnormal returns and monthly regressions, instead of quarterly, does not alter our main findings.

2.3.2. Regression Results

Table 3 reports the results of the regression in equation (4). Controlling more precisely for r_t and $r_{t-2,t-1}$, the relations between herding and future returns are essentially the same as those found using the portfolio analyses in the prior sections. Namely, as buy herds increase, returns increase in the short-term but decrease in the longer term. The reversals are again found to begin in quarter 4 and to persist through quarter 12. On the other hand, the sell-herd stocks again display no abnormal future returns.

Analogous to Table 2, Tables 4 and 5 split our sample into early and late periods, 1980 to 1992 and 1993 to 2005, respectively. The results again mirror the prior portfolio analyses. The early period in Table 4 shows evidence of a short-run positive relation for both buy and sell herding, with the sell side displaying significance in quarter 2 but not quarter 1. The longer relation between buy herding and future returns remains negative in the early period. In the late period of Table 5, the longer run relation for buy herding is still strongly negative.

2.4. Robustness Considerations

In the next few subsections, we further consider the robustness of the longer run relation between institutional buy herding and future stock returns. We examine this relation within subsamples of small and large stocks, using two alternative measures of herding, not controlling for lagged returns, and controlling for the effects of size and book-to-market equity on the right-hand side of the regression instead of the left-hand side.

2.4.1. Small and Large Stocks

Table 6 shows the regression results within small and large stocks respectively. We define small stocks as those with market capitalizations less than that of the median value across NYSE stocks in the most recent June, before the herding quarter. Large stocks are the remaining stocks. We see a negative relation between buy herding and returns over quarters 4 to 12 within both small and large subsamples.

2.4.2. Other Measures of Herding

Of the number of institutions that change their holdings of a stock in quarter t, we employ the proportion of those institutions that increase their holdings as our measure of herding in the prior sections. Here we show that our main finding of a negative relation between buy herding and future returns is obtained using an analogous share-based measure of herding as well as simply using the change in aggregate institutional ownership. Specifically, the volume-based measure is the total number of shares bought on net by all institutions that increased their positions in a given stock divided by the number of shares in that stock traded on net by all institutions, labeled $HERD_t^{Shrs}$. Institutional ownership is defined as the percentage of shares outstanding held by institutions, and its change is labeled ΔIO.

Our preferred measure of herding (equation (1)) examines the *number* of institutions that are buyers and sellers. The other two measures can be driven by a few large institutions and therefore can more easily deviate from the intended goal of capturing a preference among institutional traders to be buyers. Regardless of our inclinations, however, the other two measures each empirically predict a longer run reversal in stock returns. Again, we require at least 10 traders for each stock in quarter t.[10]

The first three columns of Table 7 examine the share-based measure and its relation to future abnormal returns. As in earlier regressions, we split the herding measure into separate buy and sell variables. We see a strong negative coefficient on buy herding using the share-based measure in years one, two, and three. In the remaining three columns, we compete the original measure, $HERD_t$, with the share-based one. Longer run reversal is better captured with the original measure, as the share-based measure no longer displays any significance.

[10] See footnote 6 for more discussion of our preferred measure of herding.

The first three columns of Table 8 examine changes in institutional ownership separated into buying and selling measures, positive ΔIO and negative ΔIO respectively. This alternative measure also predicts reversals in future returns following buy herding.[11] However, the ability of $Positive\Delta IO$ to predict longer run reversals in returns is also dominated by the explanatory power of the original measure, *BuyHERD*.

We do see some interesting differences though between these two alternative measures and *HERD*. In Table 8, changes in institutional ownership are negatively related to future returns in year one even in the presence of *HERD*. For brevity's sake we do not report each quarter separately, but neither the share-based measure nor the change in institutional ownership display any positive relation to future returns in the first few quarters. Only *BuyHERD* captures a short-run continuation in returns (see Table 3).

2.4.3. Control Variables

To further document the robustness of the longer run reversals in returns that follow buy herds, which examine two additional regression specifications. First, we remove r_t and $r_{t-2,t-1}$ as regressors. We argue earlier that these controls are important to employ, to ensure that the herding effects we find are unrelated to known lagged-return effects. However, the first two columns of Table 9 show that removing r_t and $r_{t-2,t-1}$ from the regressions does not alter the finding of longer run reversals due to buy herding, consistent with the portfolio tests in Table 1.

The second specification that we consider in Table 9 controls for book-to-market-equity and size effects on the right-hand side instead of on the left-hand side via the DGTW adjusted returns. The last two columns of Table 9 show that stocks with buy herds suffer return reversals in years two and three with this specification as well.

[11] Dasgupta, Prat, and Verardo (2007) examine stocks with persistent changes in aggregate institutional ownership over several quarters and find their returns to reverse in the future. Yan and Zhang (2009) examine short-term and long-term institutions and find that changes in holdings of only short-term institutions predict stock returns in the next year.

3. Do the herding institutions suffer the return reversals?

The prior sections document that buy herds of institutional investors negatively predict future returns. Specifically, we find that the prices of stocks with extreme buy herds fall by about 4.5% from quarter 4 to quarter 12, as shown in Table 1 and Figure 1. This return pattern lends itself to a wide array of interpretations regarding the actions of the herders themselves. On one extreme, the entering herd might be uninformed about stock valuations and unaware of the impending price declines, leaving themselves to suffer the price falls. On the other extreme, the herds of institutions might be fully informed and sophisticated investors who through their herding seek to push stock prices up only to exit the stocks ahead of the correctional declines in prices. We discuss each of these views in the following sections.

3.1. Uninformed herd

Perhaps the more straightforward interpretation of the herding is that these institutions are unaware of the impending price declines. One possible reason for their being unaware can come from the nature of the herd itself. For example, to the extent that these herds are formed on the basis of one manager following other managers, prior theoretical research shows how the resulting herd can be uninformed about the intrinsic values of the stocks they buy. The rational extraction of another trader's signal from his actions can lead subsequent traders to follow the earlier trader's actions regardless of their own valuation signals. Such an outcome impedes all information from being fully impounded into prices. See the works of Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992), Welch (1992), and Avery and Zemsky (1998) for more detail. An uninformed herd can similarly also result from the reputation-based herding noted by Scharfstein and Stein (1990). Managers who are concerned about developing or maintaining their reputations as good managers might rationally choose to mimic the actions of other managers, possibly ignoring their own signals.

3.2. Hyperinformed herd

On the other extreme, prior literature identifies the possibility that the herders are sophisticated well-informed traders despite their taking positions in stocks whose prices will soon fall. De Long, Shleifer, Summers, and Waldmann (1990) note how the presence of uninformed "noise" traders can result in sophisticated and informed investors rationally choosing to buy an overvalued stock. The reason they buy an overvalued stock today is the expectation that positive-feedback traders will be willing to buy the stock tomorrow at an even higher price. Essentially, rational investors buy to stimulate others' demand for the stock and profit at the expense of the uninformed trend chasers. Hence, the informed traders aggravate overpricing instead of correcting it. This notion goes beyond the reasoning that limits to arbitrage inhibit informed and rational investors from correcting mispricings that they know to exist, as advanced by Pontiff (1996), Shleifer and Vishny (1997), and others. Limits to arbitrage predict that the sizes of the positions taken by arbitragers are smaller than they would otherwise be, but rational investors still trade to correct mispricings.

Abreu and Brunnermeier (2003) also note that informed and rational investors might choose to aggravate mispricings. If more than one investor must trade against a "bubble" to burst it, then rational investors face a coordination problem. In light of this, rational investors who are uncertain about the actions the other rational investors will take might decide to "ride the bubble" expecting to sell the stock at a higher price in the future, as the bubble continues to grow.

Brunnermeier and Nagel (2004) provide empirical evidence consistent with sophisticated investors choosing to ride bubbles. From 1998 to 2000, they find that hedge funds increased their weights in technology stocks as the prices of those stocks rose, and then decreased their weights before the prices of those stocks fell. A portfolio tracking their trading in these stocks generates an abnormal return of 4.5% per quarter. In short, hedge funds traded these stocks as if they were aware of the overvaluations, selling before prices collapsed.[12]

Given these varied interpretations of the behaviors of the buy herders, we next examine whether these herders are better characterized as uninformed or informed traders, using their trading performances in the buy-herd stocks to distinguish these two possibilities. That is, we assume that a necessary condition for being informed is the ability to generate positive abnormal returns.

3.3. How Well do the Herders Trade the Buy-Herd Stocks?

We evaluate trading performance by forming portfolios that mimic the herders' trading of these stocks. Since institutional ownership is only reported at quarter end, we cannot determine precisely when their trades occur within the quarter. Therefore, we examine the two extreme scenarios whereby trading in all quarters occurs either at the beginning of the period or at the end.

Specifically, we identify the buy-herd stocks each calendar quarter as those in the top decile of $HERD_t$. We then identify every institution buying these stocks in that quarter and track their aggregate current and future positions in these stocks. We form a portfolio comprised of these aggregate positions, where the weights are based on the dollar values of the positions held by the herding institutions. The performances of these portfolios are determined in calendar time over various event windows, as in earlier sections.

Table 10 provides the abnormal returns of these portfolios mimicking the trading of the herding institutions. Panel A reports results for the full sample, 1980 to 2005; Panel B for the early period, 1980 to 1992; Panel C for the late period, 1993 to 2005. Assuming either beginning-of-period (BOP) trading or end-of-period (EOP) trading, Panel A reveals no evidence of positive abnormal returns. That is, the herding institutions are not trading these buy-herd stocks well. We can say no more than this as evidence of

[12] The conclusion that a bubble existed in tech stocks in the late 1990s is debatable. Pastor and Veronesi (2006) question whether NASDAQ prices ex ante were too high in the late 1990s.

negative abnormal returns are not robust across the BOP and EOP methods. The early and late periods also lack robust evidence of abnormal returns.

We also consider the performances of two groups of other investors and examine how each fares in their trading of the buy-herd stocks. The two trader groups are: 13F institutions not buying with the herd in quarter t and non-13F traders. We label the first group as "other" institutions, and the second as "individual" investors. The trading of the individual investors is determined as the complement of the trading recorded in the 13F data.[13]

Panel A of Table 10 indicates that the evidence on the performances of the other, non-herding institutions' portfolios of buy-herd stocks is also mixed. On one hand, the BOP analysis finds positive alphas in the two years after the herding quarter. On the other, the EOP method finds only evidence of negative abnormal returns in year 3. The early and late periods display no robust alphas either. Hence, we can make no clear conclusion.

Panel A of Table 10 also shows the performances of individual investors. For this group the evidence is clear: Individual investors are strongly hurt by their trading of these buy-herd stocks. Individual investors suffer negative alphas assuming either BOP or EOP trading. The negative alphas for individual investors are robustly evident in each of the subperiods as well. Moreover, in untabulated results, we identify a benchmark no-trade portfolio which maintains the stock positions held in quarter t for the aggregate individual-investor portfolio. Using this no-trade portfolio, we can see that individual investors make themselves significantly worse off in their subsequent trading of the buy-herd stocks. After quarter t, they increase their positions in stocks that will perform poorly in the future. Specifically, over the full period, the actual portfolio for individual investors underperforms its no-trade benchmark over quarters 1 to 12 by 0.20% per quarter using EOP and by 0.72% per quarter using BOP, with t-statistics greater than 3.9 in each case. The finding that the post-herd trading of individual investors make

[13]This complement is more than just trading by individual investors, as it includes small institutions managing less than $100 million, small institutional positions of less than $200,000 and less than 10,000 shares, and institutional short selling.

themselves worse off is also evident in each of the subperiods, with t-statistics greater than 2.16 in each of the four cases (BOP/early, EOP/early, BOP/late, EOP/late).

Finally, we note that controlling for r_t and $r_{t-2,t-1}$ with the sorting procedure described in section (2.2) also leaves no robust conclusions across BOP and EOP trading for the herding and non-herding institutions, but once again, individual investors incur significantly negative abnormal returns across both BOP and EOP trading.

Without higher frequency trade data, we are admittedly limited in what we can say regarding the trading acumen of investors in the buy-herd stocks. The evidence using quarterly data, however, does strongly suggest that individual investors make themselves worse off by buying buy-herd stocks whose prices will subsequently fall. Why individual investors pursue these buy-herd stocks is an interesting avenue for further research.

4. Conclusion

We find that buy herds predict negative abnormal stock returns two and three years after the herding. This result suggests that buy herds trigger overvaluations, warranting a correction. Our finding consequently alters the perception of institutional herding as benefiting price discovery, as the extant literature concludes. The evidence we detect of institutions' having deleterious effects on stock prices (when they herd together to buy) echoes the messages of recent studies examining institutions in other settings. For example, Dasgupta, Prat, and Verardo (2007), Gutierrez and Pirinsky (2007), and Shu (2007) link aggregate institutional trading to various cases of presumed stock mispricings. These studies suggest, as we do, that some trading by institutions reliably drives prices away from intrinsic values. Moreover, as discussed in these prior studies as well, such trading can be a rational consequence of agency issues in money management or of the presence of "noise" traders in the stock market. Further research to identify and isolate why institutions trade as they do in these various circumstances is warranted.

On the sell side, in contrast to prior studies, we find that sell herds do not predict future returns. While sell herds predicted return continuations in the early part of the sample period, they have no explanatory power for future returns after 1992, nor for the full period.

Our asymmetric findings for buy and sell herds seemingly contrast with the asymmetries found in studies of daily and weekly institutional trading where return reversals are found in the days following an institutional sell, but not following a buy. That is, the price impact of a sell is temporary while the impact of a buy is permanent. See the works of Kraus and Stoll (1972b), Chan and Lakonishok (1995), Kaniel, Saar, and Titman (2006) and Campbell, Ramadorai, and Schwartz (2007). We suspect that these high-frequency results are related to ours. On the buy side, the accumulation of the price impacts of a herd of buys over a quarter should seemingly result in a sizable price increase, which warrants a future correction in the stock's price. On the sell side, the accumulated price impacts of a herd of sells should remain small as the price impacts of each trade typically reverse, requiring no future correction. Of course, these statements remain conjectures at this point, and we leave their investigation to future research.

A second conjecture is that short-sale constraints might also contribute to the asymmetries we find across buy and sell herds. These constraints diminish the market's ability to adjust prices downward following a sell herd, which in this case might be a good thing.

We also examine the trading acumen of the herding institutions regarding the stocks into which they herd. We fail to find robust evidence of the herders' profiting from their herding. Beyond that, the evidence on the alphas of their portfolios of buy-herd stocks is a mixed bag of inferences, as are the alphas on the other, non-herding institutions' portfolios of buy-herd stocks. However, we find strong evidence that individual investors bear the brunt of the poor performances of these buy-herd stocks. Future examinations of performance with high-frequency data might shed more light on the trading dynamics highlighted here.

A. Appendix

A.1. 13F data in more detail

From Thomson's data on the 13F filings of institutions, we identify all stocks with CRSP data, matching first on cusip and then on ticker. Thomson provides a change variable which tracks split-adjusted changes in each institution's holdings. For 24,605,585 stock/institution/quarters, $SHS_t - CHG_t = SHS_{t-1}$, where SHS_t is the number of shares held in a given stock at the end of quarter t (with the stock subscript i and the institutional subscript m suppressed) and CHG_t is Thomson's determined change in the number of shares held this quarter from the last quarter, adjusted for stock splits. When $SHS_t = CHG_t$, we label these entries by a given institution into the stock. There are 4,070,465 entries. The remaining, discrepant observations are reexamined using split factors from CRSP. 726,774 of these discrepancies are due to splits in quarter t, confirming that CHG_t is correctly accounting for the split. For 732,574 observations we cannot reconcile SHS_t and CHG_t with SHS_{t-1}. For these records, we leave SHS_t and CHG_t at their reported levels.[14]

For reasons we do not know, the Thomson data at times are missing filings for an institution in quarter t but the filing for quarter $t+1$ and CHG_{t+1} is not missing. So we have the opportunity to backfill observations. Thomson also provides the prior report date from which their change variable is determined, though it is not well populated until June 2000. For the cases where a hole occurs in the time-series of an institutions filings, we proceed as follows. For June 2000 and later, if the first available data after the hole, quarter $t+1$, states the prior report date to be quarter t, we then backfill the holdings for quarter t using SHS_{t+1}, CHG_{t+1}, and split factors in quarter $t+1$. This enables us to recover CHG_t if SHS_{t-1} is available. If SHS_{t-1} is missing we do not

[14] One reason for our decision to trust the data in these discrepant cases is that we find instances where an institution reports its holdings together with a parent or related institution. We confirm that the changes are correctly determined using the aggregate holdings from the two separate reports for the prior quarter. These are clearly cases where $SHS_t - CHG_t \neq SHS_{t-1}$ for the single filer in quarter t.

assume that a stock entry occurred in quarter t; instead, we set CHG_t to missing.[15] For March 2000 and earlier, we do the same if the prior report date is given. If it is not given, we identify the institutions with only one-quarter holes in their time series; we assume that the prior report date is the previous quarter and backfill the holdings as just described.[16]

There are 769,938 observations where the prior quarter's filing is missing, but the filing from two quarters ago is not. From these, 768,109 observations are recovered; when data for the stock on CRSP is not available in quarter $t-1$, we do not backfill. Also when backfilling, we impose the filter that SHS_t be nonnegative, setting the 148 observations that fail this filter to missing. Finally, 938,311 observations are missing lagged holdings and are not backfilled because it is the first time-series quarter for the institution or the reporting gap for the institution is longer than one quarter.

We identify 3,534,387 exits of a given stock by a given institution. These are defined when (i) the institution held shares in the stock last quarter, (ii) there is no record of that institution holding any shares of the stock this quarter, and (iii) that institution filed a 13F in this quarter. Our final sample contains 36,146,143 observations of SHS_t, and 36,039,486 observations of CHG_t.

[15] See footnote 14.

[16] The prior report date is the previous quarter in 99.2% of the observations with nonmissing data for the prior report date. Conditional on a one-quarter hole in an institution's time series of filings, the frequency is 95.6%.

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Table 1
Abnormal Returns of Stocks with Extreme Buy or Sell Herds
1980–2005

Each quarter of 1980 to 2005, we sort stocks into deciles based on $HERD_t$, the number of institutions that are net buyers of a given stock during quarter t divided by the number of institutions with net changes in their holdings of that stock. Stocks with less than ten institutions making net changes in holdings during quarter t are excluded. Stocks in the highest decile of $HERD_t$ form an equally weighted portfolio denoted the "buy herd". For each stock in this portfolio, we calculate quarterly abnormal stock returns (adjusted for size, book-to-market equity, and prior one-year-return using $5 \times 5 \times 5$ portfolios). The "sell herd" portfolio is formed analogously using the bottom decile of $HERD_t$. To examine multiquarter event windows, we form calendar-time portfolios. The absolute value of the t-statistic is in parentheses. Quarterly alpha estimates are multiplied by 100.

	Qtr -2	Qtr -1	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtrs 5 – 8	Qtrs 9 – 12
Buy	6.68	8.82	10.97	0.80	−0.05	−0.26	−0.75	−0.59	−0.42
	(14.67)	(14.30)	(12.04)	(2.45)	(0.19)	(1.23)	(3.63)	(2.83)	(2.23)
Sell	−4.05	−5.91	−7.11	−0.61	−0.48	−0.21	0.02	0.16	0.03
	(9.28)	(11.04)	(13.67)	(1.39)	(1.29)	(0.63)	(0.06)	(0.74)	(0.13)
Buy−Sell	10.72	14.73	18.01	1.41	0.44	−0.05	−0.77	−0.76	−0.45
	(14.44)	(14.36)	(13.97)	(2.19)	(0.90)	(0.12)	(2.29)	(2.39)	(1.52)

Table 2
Abnormal Returns of Stocks with Extreme Buy or Sell Herds
Subperiods

Each quarter we sort stocks into deciles based on $HERD_t$, the number of institutions that are net buyers of a given stock during quarter t divided by the number of institutions with net changes in their holdings of that stock. Stocks with less than ten institutions making net changes in holdings during quarter t are excluded. Stocks in the highest decile of $HERD_t$ form an equally weighted portfolio denoted the "buy herd". For each stock in this portfolio, we calculate quarterly abnormal stock returns (adjusted for size, book-to-market equity, and prior one-year-return using $5 \times 5 \times 5$ portfolios). The "sell herd" portfolio is formed analogously using the bottom decile of $HERD_t$. To examine multiquarter event windows, we form calendar-time portfolios. The absolute value of the t-statistic is in parentheses. Quarterly alpha estimates are multiplied by 100. In Panel A, we form portfolios each quarter from 1980 to 1992, and in Panel B, from 1993 to 2005.

	Qtr -2	Qtr -1	Qtr 0	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtrs 5 – 8	Qtrs 9 – 12
Panel A. 1980 to 1992									
Buy	5.05	6.08	7.50	1.09	0.15	−0.12	−0.57	−0.50	−0.24
	(10.31)	(12.13)	(12.81)	(2.99)	(0.47)	(0.47)	(2.39)	(2.16)	(1.18)
Sell	−2.17	−2.70	−4.75	−1.02	−1.03	−0.58	−0.48	−0.21	−0.16
	(7.36)	(6.35)	(11.17)	(2.88)	(3.74)	(1.85)	(1.62)	(0.98)	(0.61)
Panel B. 1993 to 2005									
Buy	8.30	11.57	14.45	0.51	−0.26	−0.40	−0.94	−0.62	−0.59
	(11.83)	(11.62)	(9.07)	(0.92)	(0.65)	(1.20)	(2.74)	(1.74)	(1.71)
Sell	−5.93	−9.12	−9.47	−0.20	0.08	0.18	0.56	0.62	0.36
	(8.04)	(12.06)	(11.38)	(0.24)	(0.12)	(0.31)	(1.20)	(1.59)	(0.94)

Table 3
Regressions of Future Abnormal Stock Returns on Herding

Each quarter from 1980 to 2005, we regress various windows of future quarterly stock returns (adjusted for size, book-to-market equity, and prior one-year return using $5 \times 5 \times 5$ portfolios) on $BuyHERD_t$, $SellHERD_t$ and two horizons of lagged returns. $BuyHERD_t$ is equal to $HERD_t$ if $HERD_t$ is greater than or equal to the cross-sectional median of $HERD$ in quarter t and zero otherwise, where $HERD_t$ is defined in Table 2. $SellHERD_t$ is equal to $HERD_t$ if $HERD_t$ is less than the cross-sectional median of $HERD$ in quarter t and zero otherwise. DUM_t^{Buy} is a dummy variable set to one when $HERD_t$ is greater than or equal to the cross-sectional median of $HERD$ in quarter t and zero otherwise. Stocks with less than ten institutions making net changes in holdings during quarter t are excluded. Raw returns over quarter t and over quarters $[t-2, t-1]$ are denoted r_t and $r_{t-2,t-1}$ respectively. In addition, the standard errors are clustered by calendar quarter when the future-return window exceeds one quarter. The absolute values of the t-statistics are in parentheses. Coefficient estimates are multiplied by 100.

	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtrs 5 – 8	Qtrs 9 – 12
$BuyHERD_t$	3.66	−1.65	−1.06	−3.26	−2.85	−2.35
	(2.59)	(1.41)	(1.02)	(3.56)	(4.01)	(3.19)
$SellHERD_t$	1.17	0.74	0.49	0.11	−0.27	1.54
	(0.62)	(0.50)	(0.31)	(0.07)	(0.27)	(1.64)
r_t	0.28	1.91	2.52	1.53	0.24	−0.28
	(0.28)	(2.48)	(3.18)	(2.63)	(0.73)	(0.65)
$r_{t-2,t-1}$	1.95	1.51	−0.07	−0.81	−0.07	−0.25
	(3.69)	(3.33)	(0.21)	(2.14)	(0.24)	(0.63)
Intercept	−1.07	−0.60	−0.19	−0.05	0.23	−0.59
	(1.26)	(0.86)	(0.26)	(0.08)	(0.49)	(1.35)
DUM_t^{Buy}	−1.42	1.21	0.75	1.74	1.39	2.03
	(1.14)	(1.24)	(0.84)	(1.90)	(2.26)	(3.08)
Avg N	2539	2484	2433	2381	2258	2069
Avg R^2	0.02	0.01	0.01	0.01	0.01	0.01

Table 4
Regressions of Future Abnormal Stock Returns on Herding
1980 – 1992

We follow the same procedure as Table 3 but only consider herding (and other regressors) in the quarters from 1980 to 1992. The dependent variable extends beyond 1992 as needed. Standard errors are clustered by calendar quarter when the future-return window exceeds one quarter. The absolute values of the t-statistics are in parentheses. Coefficient estimates are multiplied by 100.

	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtrs 5 – 8	Qtrs 9 – 12
$BuyHERD_t$	5.33	−0.79	−0.78	−2.01	−2.38	−1.37
	(3.69)	(0.58)	(0.76)	(2.04)	(3.12)	(1.76)
$SellHERD_t$	2.79	3.64	2.58	1.84	0.39	1.25
	(1.22)	(2.41)	(1.29)	(1.00)	(0.39)	(1.13)
r_t	0.28	1.73	3.72	3.26	0.82	0.18
	(0.24)	(1.39)	(3.83)	(4.00)	(1.89)	(0.29)
$r_{t-2,t-1}$	2.47	2.64	0.74	−0.72	0.15	0.16
	(3.23)	(4.49)	(1.38)	(1.36)	(0.34)	(0.26)
Intercept	−1.74	−2.12	−1.24	−0.86	−0.21	−0.68
	(1.79)	(3.30)	(1.37)	(1.01)	(0.41)	(1.24)
DUM_t^{Buy}	−1.45	2.21	1.65	1.79	1.47	1.29
	(1.02)	(2.40)	(1.58)	(1.92)	(2.45)	(1.66)
Avg N	1763	1742	1720	1699	1648	1569
Avg R^2	0.02	0.02	0.01	0.01	0.01	0.01

Table 5
Regressions of Future Abnormal Stock Return on Herding
1993 – 2005

We follow the same procedure as Table 3 but only consider herding (and other regressors) in the quarters from 1993 to 2005. Standard errors are clustered by calendar quarter when the future-return window exceeds one quarter. The absolute values of the t-statistics are in parentheses. Coefficient estimates are multiplied by 100.

	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtrs 5 – 8	Qtrs 9 – 12
$BuyHERD_t$	1.95	−2.55	−1.35	−4.62	−3.39	−3.59
	0.80	(1.32)	(0.73)	(2.94)	(2.70)	(2.70)
$SellHERD_t$	-0.47	−2.28	−1.72	−1.77	−1.02	1.89
	(0.16)	(0.90)	(0.69)	(0.77)	(0.58)	(1.20)
r_t	0.27	2.11	1.24	−0.35	−0.42	−0.86
	(0.17)	(2.32)	(0.99)	(0.46)	(0.85)	(1.43)
$r_{t-2,t-1}$	1.42	0.34	−0.92	−0.92	−0.33	−0.76
	(1.95)	(0.51)	(2.67)	(1.65)	(0.83)	(1.78)
Intercept	−0.38	0.98	0.91	0.82	0.73	−0.47
	(0.27)	(0.80)	(0.75)	(0.76)	(0.92)	(-0.68)
DUM_t^{Buy}	−1.39	0.17	-0.21	1.68	1.30	2.97
	(0.67)	(0.10)	(0.14)	(1.03)	(1.15)	(2.68)
Avg N	3329	3256	3188	3120	2954	2696
Avg R^2	0.02	0.01	0.01	0.01	0.01	0.01

Table 6
Regressions of Future Abnormal Stock Returns on Herding within Small and Large Stocks

We follow the same procedure as Table 3 but estimate regressions within two subsets of stocks, small and large. Small stocks are those with market capitalizations less than that of the median value across NYSE stocks in the most recent June, before the herding quarter. Large stocks are the remaining stocks. Standard errors are clustered by calendar quarter. The absolute values of the t-statistics are in parentheses. Coefficient estimates are multiplied by 100.

	Small Stocks			Large Stocks		
	Qtrs 1 – 4	Qtrs 5 – 8	Qtrs 9 – 12	Qtrs 1 – 4	Qtrs 5 – 8	Qtrs 9 – 12
$BuyHERD_t$	−0.33	−2.48	−2.69	−0.65	−3.07	−2.40
	(0.40)	(3.32)	(3.18)	(0.45)	(2.10)	(1.89)
$SellHERD_t$	1.20	0.44	1.24	−2.23	−1.57	1.15
	(0.98)	(0.39)	(1.33)	(1.17)	(1.03)	(0.74)
r_t	1.83	0.32	−0.23	0.79	0.22	−0.12
	(3.79)	(0.89)	(0.51)	(1.27)	(0.50)	(0.23)
$r_{t-2,t-1}$	0.61	−0.04	−0.37	0.72	−0.03	−0.01
	(2.05)	(0.13)	(0.89)	(1.99)	(0.08)	(0.02)
Intercept	−0.87	−0.17	−0.50	1.05	0.87	−0.43
	(1.54)	(0.33)	(1.17)	(1.21)	(1.18)	(0.61)
DUM_t^{Buy}	0.80	1.57	2.26	−0.92	0.88	1.83
	(0.98)	(2.03)	(3.02)	(0.82)	(0.84)	(1.86)
Avg N	1597	1433	1282	863	824	787
Avg R^2	0.01	0.01	0.01	0.02	0.02	0.02

Table 7
Regressions of Future Abnormal Stock Return on Share-Based Measure of Herding

We follow the same procedure as Table 3 but consider two new regressors, $BuyHERD_t^{Shrs}$ and $SellHERD_t^{Shrs}$. These measures are formed from $HERD_t^{Shrs}$ analogously to how $BuyHERD_t$ and $SellHERD_t$ are formed from $HERD_t$, where $HERD_t^{Shrs}$ is the number of shares bought on net by institutions in quarter t divided by the number of shares traded on net by institutions. In the first three columns, DUM_t^{Buy} equals one when $HERD_t^{Shrs}$ is greater than or equal to the cross-sectional median of $HERD^{Shrs}$ in quarter t and zero otherwise. In the last three columns, DUM_t^{Buy} equals one when $HERD_t$ is greater than or equal to the cross-sectional median of $HERD$ in quarter t and zero otherwise. Standard errors are clustered by calendar quarter. The absolute values of the t-statistics are in parentheses. Coefficient estimates are multiplied by 100.

	Qtrs 1 – 4	Qtrs 5 – 8	Qtrs 9 – 12	Qtrs 1 – 4	Qtrs 5 – 8	Qtrs 9 – 12
$BuyHERD_t^{Shrs}$	−1.13	−1.87	−1.22	−0.01	−0.33	−0.31
	(2.38)	(4.23)	(2.39)	(0.04)	(1.07)	(1.10)
$SellHERD_t^{Shrs}$	1.43	−0.17	0.35	0.59	−0.48	−0.30
	(1.95)	(0.26)	(0.55)	(1.47)	(1.21)	(0.79)
$Buy\ HERD_t$				−0.08	−2.61	−1.98
				(0.11)	(3.58)	(2.70)
$Sell\ HERD_t$				0.55	0.02	1.74
				(0.49)	(0.02)	(1.90)
r_t	1.61	0.16	−0.26	1.61	0.24	−0.26
	(3.26)	(0.48)	(0.59)	(3.33)	(0.74)	(0.60)
$r_{t-2,t-1}$	0.65	−0.12	−0.26	0.67	−0.07	−0.25
	(2.34)	(0.38)	(0.66)	(2.44)	(0.23)	(0.63)
Intercept	−0.73	0.10	−0.05	−0.60	0.30	−0.54
	(2.51)	(0.36)	(0.19)	(1.07)	(0.63)	(1.19)
DUM_t^{Buy}	1.14	1.04	0.85	0.30	1.39	1.94
	(2.25)	(2.26)	(1.76)	(0.42)	(2.31)	(3.01)
Avg N	2460	2258	2069	2460	2258	2069
Avg R^2	0.01	0.01	0.01	0.01	0.01	0.01

Table 8
Regressions of Future Abnormal Stock Returns on Changes in Institutional Ownership

We follow the same procedure as Table 3 but consider two new regressors, *Positive* ΔIO_t and *Negative* ΔIO_t . These measures are formed from ΔIO_t analogously to how $BuyHERD_t$ and $SellHERD_t$ are formed from $HERD_t$, where ΔIO_t is the change in the percentage of outstanding shares held by institutions. In the first three columns, DUM_t^{Buy} equals one when ΔIO_t is greater than or equal to the cross-sectional median of ΔIO in quarter t and zero otherwise. In the last three columns, DUM_t^{Buy} equals one when $HERD_t$ is greater than or equal to the cross-sectional median of *HERD* in quarter t and zero otherwise. Standard errors are clustered by calendar quarter. The absolute values of the t-statistics are in parentheses. Coefficient estimates are multiplied by 100.

	Qtrs 1 – 4	Qtrs 5 – 8	Qtrs 9 – 12	Qtrs 1 – 4	Qtrs 5 – 8	Qtrs 9 – 12
Positive ΔIO_t	−3.84	−4.65	−1.65	−4.78	−2.62	−0.47
	(2.07)	(2.44)	(0.90)	(2.60)	(1.30)	(0.24)
Negative ΔIO_t	3.15	−0.17	2.67	1.97	0.55	1.83
	(1.24)	(0.06)	(1.10)	(0.85)	(0.21)	(0.76)
$BuyHERD_t$				0.35	−2.47	−2.28
				(0.50)	(3.14)	(2.71)
$SellHERD_t$				0.47	−0.24	1.38
				(0.42)	(0.24)	(1.41)
r_t	1.70	0.15	−0.30	1.67	0.27	−0.30
	(3.44)	(0.44)	(0.66)	(3.47)	(0.78)	(0.68)
$r_{t-2,t-1}$	0.70	−0.09	−0.27	0.71	−0.04	-0.25
	(2.47)	(0.28)	(0.66)	(2.59)	(0.13)	(0.63)
Intercept	−0.13	0.01	0.12	−0.37	0.23	−0.51
	(0.95)	(0.08)	(0.81)	(0.72)	(0.48)	(1.09)
DUM_t^{Buy}	−0.08	0.04	−0.06	0.00	1.20	1.92
	(1.23)	(0.47)	(0.90)	(0.01)	(1.81)	(2.74)
Avg N	2460	2258	2069	2460	2258	2069
Avg R^2	0.01	0.01	0.01	0.02	0.01	0.01

Table 9
Other Regression Specifications

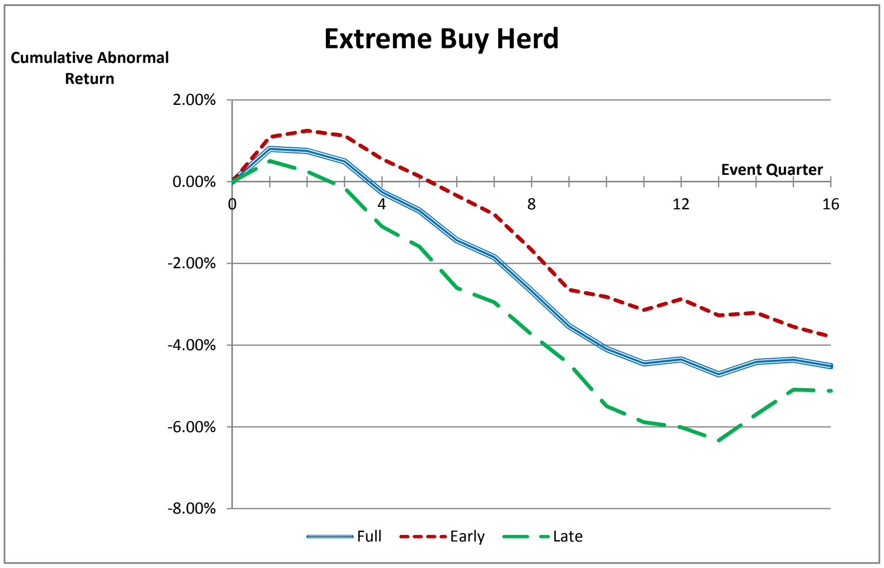
We follow the same procedure as Table 3 but consider two alternative regressions. The first two columns regress future abnormal returns, AR_{t+k}, on the herding measures but not on raw returns contemporaneous to the herding and two quarters prior, r_t and $r_{t-2,t-1}$ respectively. The last two columns regress raw future returns, R_{t+k}, on the herding and other measures including $\log(BM_t)$ and $\log(Size_t)$. Standard errors are clustered by calendar quarter. The absolute values of the t-statistics are in parentheses. Coefficient estimates are multiplied by 100.

	AR_{t+k}		R_{t+k}	
	Qtrs 5 − 8	Qtr 9 − 12	Qtrs 5 − 8	Qtrs 9 − 12
$BuyHERD_t$	−3.05	−2.61	−2.95	−1.70
	(3.76)	(3.05)	(3.62)	(2.28)
$SellHERD_t$	−0.37	1.11	−1.76	1.51
	(0.33)	(0.97)	(1.20)	(1.32)
r_t			−1.12	−0.98
			(1.91)	(1.59)
$r_{t-2,t-1}$			−1.15	−0.65
			(2.43)	(1.25)
$\log(BM_t)$			0.59	0.40
			(1.77)	(1.10)
$\log(Size_t)$			−0.07	−0.05
			(0.35)	(0.26)
Intercept	0.26	−0.43	2.40	0.42
	(0.47)	(0.76)	(0.95)	(0.17)
DUM_t^{Buy}	1.45	1.96	0.70	1.68
	(2.24)	(2.76)	(0.79)	(2.36)
Avg N	2259	2070	2223	2042
Avg R^2	0.00	0.00	0.04	0.04

Table 10
How Well Do Investors Trade the Buy-Herd Stocks?

Each quarter from 1980 to 2005, we identify the stocks in the top decile of $HERD_t$, defined in Table 1. Using the abnormal returns of these buy-herd stocks (adjusted for size, book-to-market, and prior one-year return using $5 \times 5 \times 5$ portfolios), we evaluate how well the herding institutions trade these stocks. An aggregate portfolio of buy-herd stocks is formed each quarter, and their performances over various holding periods are evaluated using a calendar-time method. The amount invested by all the herding institutions in each buy-herd stock relative to the amount invested by these institutions across the set of buy-herd stocks forms the portfolio's weights. An aggregate portfolio for the institutions not buying in quarter t, the "other institutions," and an aggregate portfolio for the complement of the 13F holdings, the "individuals," are formed analogously. Panel A reports results for the full period, Panel B for 1980 to 1992, and Panel C for 1993 to 2005. The absolute value of the t-statistics are in parentheses. Quarterly alpha estimates are multiplied by 100.

	BOP			EOP		
	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 9 − 12	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 9 − 12
Panel A. 1980 to 2005						
Herding Institutions	0.28	0.00	−0.40	−0.04	−0.28	−0.72
	(0.94)	(0.01)	(1.22)	(0.10)	(1.10)	(2.19)
Other Institutions	0.93	0.53	−0.09	0.11	−0.12	−0.68
	(2.79)	(2.19)	(0.29)	(0.32)	(0.47)	(2.21)
Individuals	−0.85	−0.95	−1.33	−0.36	−0.51	−0.81
	(3.16)	(4.04)	(4.83)	(1.50)	(2.31)	(3.02)
Panel B. 1980 to 1992						
Herding Institutions	0.32	−0.11	−0.04	0.11	−0.33	−0.27
	(1.09)	(0.38)	(0.11)	(0.37)	(1.19)	(0.86)
Other Institutions	0.72	0.20	0.43	0.33	−0.35	−0.04
	(2.06)	(0.77)	(1.38)	(0.10)	(1.36)	(0.13)
Individuals	−0.31	−0.73	−0.50	−0.06	−0.44	−0.18
	(1.55)	(2.89)	(2.43)	(0.29)	(1.82)	(0.89)
Panel C. 1993 to 2005						
Herding Institutions	0.26	0.05	−0.63	−0.16	−0.30	−1.07
	(0.49)	(0.13)	(1.00)	(0.26)	(0.67)	(1.72)
Other Institutions	1.11	0.84	−0.52	0.18	0.09	−1.28
	(1.96)	(2.02)	(0.91)	(0.31)	(0.21)	(2.28)
Individuals	−1.43	−1.20	−2.22	−0.70	−0.57	−1.44
	(2.92)	(3.00)	(4.17)	(1.58)	(1.55)	(2.70)



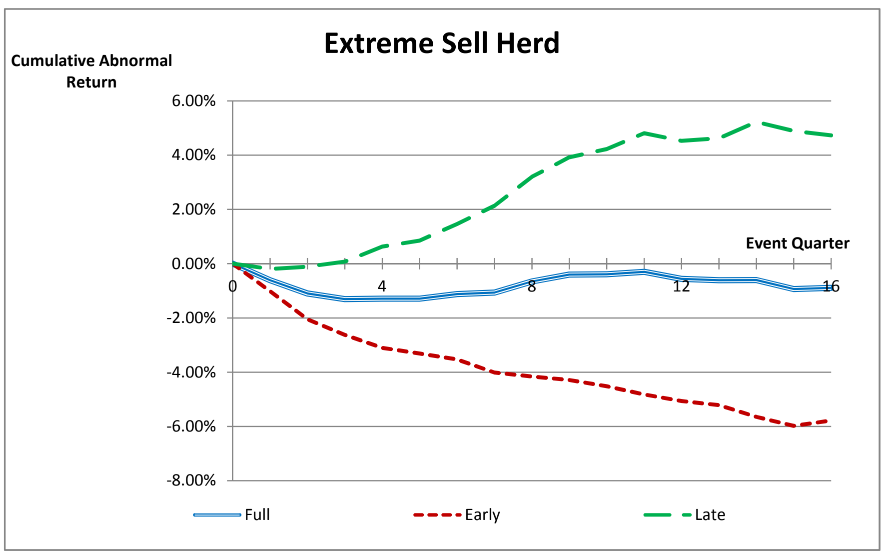
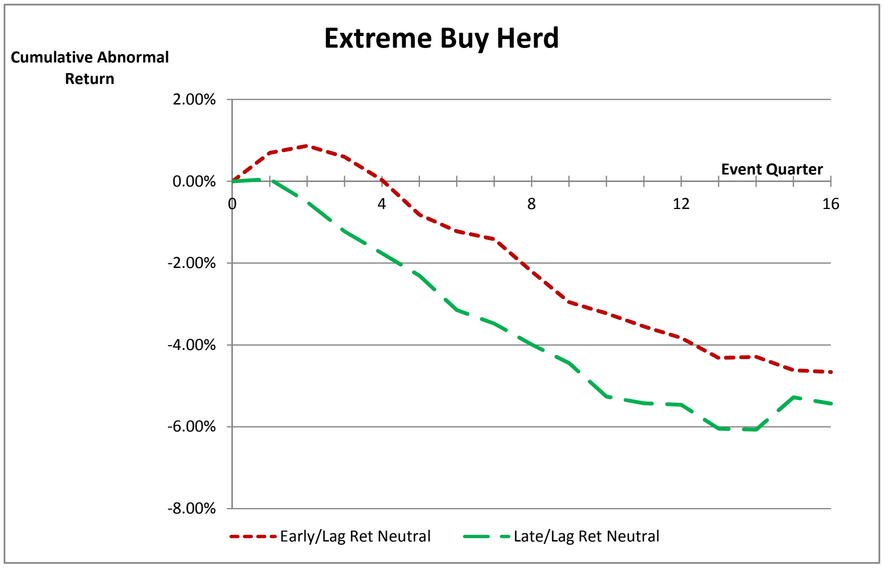


Figure 1: Each quarter from 1980 to 2005, we identify the stocks in the highest decile of $HERD_t$ and the lowest decile, where $HERD_t$ is defined as the number of institutions that are net buyers of a given stock during quarter t divided by the number of institutions with net changes in their holdings of that stock. Abnormal returns for these stocks are estimated each month controlling for size, book-to-market equity, and prior one-year return using $5 \times 5 \times 5$ portfolios. These abnormal returns are averaged each event quarter for the highest and lowest deciles respectively, and the cumulative abnormal returns are plotted. The top figure is the plot for the stocks in the extreme buy herd, and the bottom is for the stocks in the extreme sell herd. The full-period plots as well as the early (1980 – 1992) and late (1993 – 2005) are shown.



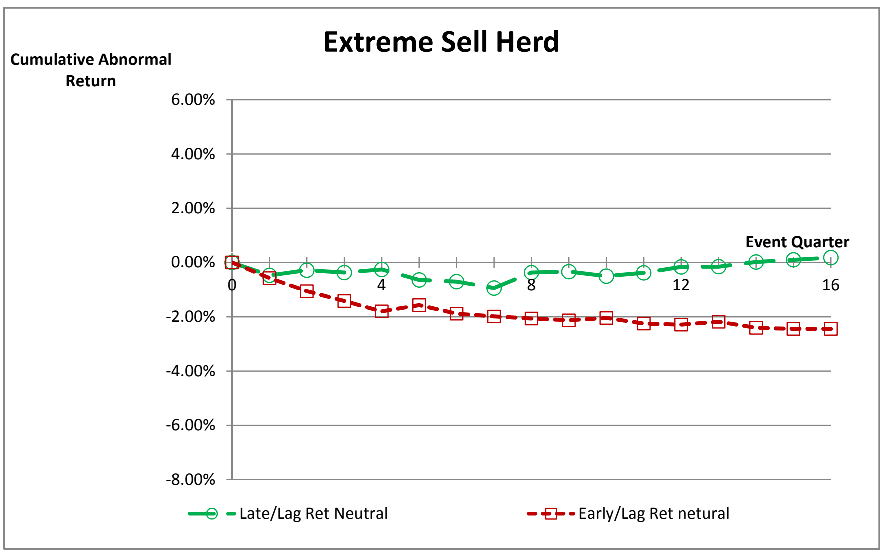


Figure 2: These plots are similar to Figure 1 except that these portfolios also control for raw returns in quarter t and raw returns over quarters $[t-2, t-1]$ using the following sorting procedure. Each quarter stocks are first sorted into quintiles based on r_t. We then sort each of these five portfolios into five further portfolios based on $r_{t-2,t-1}$. Lastly, we sort each of these 25 portfolios into deciles based on $HERD_t$. Each calendar quarter, we form an equally weighted portfolio of all stocks in the 25 portfolios with the largest values of $HERD_t$. The abnormal returns of this portfolio estimate the performances of the extreme buy-herd stocks controlling for both r_t and $r_{t-2,t-1}$ in addition to size, book-to-market equity and one year prior return. We do the analogous procedure for the extreme sell-herd stocks. Only the early period (1980 – 1992) and the late period (1993 – 2005) are shown.