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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 concludes that herding promotes price discovery. That is, herding correctly predicts stock returns in the near term. Examining a longer window, we find that herding is negatively related to returns in the second year after the herding. This longer run reversal in returns dominates any shorter run return continuation and suggests that herding pushes prices beyond their intrinsic levels. In addition, consistent with a price pressure interpretation of the longer run reversal, we detect an asymmetry in the relations between buy and sell herding and longer run reversal that mirrors the well-documented buy/sell asymmetry found in the high-frequency studies of institutional trades. Buy herds during up markets push prices too high; sell herds during down markets push prices too low.

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]

Studies of institutional trades, using trade-by-trade data, find that the typical trade moves prices (Kraus and Stoll (1972b), Chan and Lakonishok (1995), Kaniel, Saar, and Titman (2008), Campbell, Ramadorai, and Schwartz (2009)). In this study, we are interested in the effect of a herd of institutional trades 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.

[1] Institutional ownership is estimated from 13F filings provided by Thomson Financial. The trading volume estimates come from Kaniel, Saar, and Titman (2008) 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.

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

However, a longer run analysis of whether future returns reverse after the herding is warranted. We learn from other literatures on stock returns that presumed correctional reversals in returns 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 in the second year after the herding. That is, stocks with extreme buy herds (upper decile) underperform stocks with extreme sell herds (lower decile) by about 4% to 8% in year two, depending on the model specification. This return reversal is evident also in cross-sectional regressions

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

identifying a sensitivity of future returns to variations in herding, across a variety of performance metrics, and not just in the smallest stocks.[4]

The longer run return reversal that we detect dominates any shorter run return continuation following a herd. Specifically, we find that abnormal returns are negative across quarters 1 to 8 after the herding. Our findings stand in contrast to the extant view that institutional herding serves only to benefit price discovery. The return reversal suggests that institutional herding results in stock prices that reliably deviate from intrinsic levels, warranting the future return reversal.

Our findings differ from those of Wermers (1999) and Sias (2004) simply because we examine a longer post-herding window. Return reversal in the second year after herding is evident in the earlier sample period they examine, as well as in recent years. In contrast, the short run return continuation found by Wermers (1999) and Sias (2004) is isolated to the sample period they study. Brown, Wei, and Wermers (2008) also find this lack of return continuation in recent years using the herding of mutual fund trades, but they do not study the longer run reversal that we focus on.[5]

Given that institutional herding leads to a future return reversal, we interpret herding to push stock prices excessively. In the high-frequency literature on the price impact of institutional trades, the well-documented asymmetry in the price impact of a buy versus a sell predicts an asymmetry in the longer run return reversal we document. The trade-by-trade studies find that a buy of an institution pushes prices farther than a sell, and that a sell's price impact tends to largely

[4]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 longer run return reversal. However, the proportion of buyers dominates ΔIO as a predictor of longer 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.

[5]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 effect of herding, which is our focus.

reverse in a few days (Kraus and Stoll (1972b), Chan and Lakonishok (1995), Kaniel, Saar, and Titman (2008), Campbell, Ramadorai, and Schwartz (2009)). To the extent that our findings are driven by the price impact of institutional trades, stocks with buy herds should have their prices pushed farther from intrinsic levels than stocks with sell herds. Consistent with this, we find an asymmetry in the return reversal across buy and sell herds. Returns robustly reverse after a buy herd, but do not do so after a sell herd.

In addition, Chiyachantana, Jain, Jiang, and Wood (2004) find that the buy/sell asymmetry in the price impact of institutional trades depends on stock market conditions. Buys have greater price impact in up markets while sells have greater price impact in down markets. We examine the link between our longer run return reversal and stock market conditions. The market's return in the herding quarter predicts whether the buy side or the sell side will reverse. Buy herds in up markets produce return reversal; sell herds in down markets produce reversal. The ability to predict the time-series variation in return reversal is not due to a cyclicality in the market's risk premium.

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 discovery to a presumed trigger of mispricings which require the future reversal in returns. Given that our results mirror those from the high-frequency studies of the price impacts of institutional trades, it seems that the herding of institutional trades pushes prices beyond their intrinsic levels. Future research with higher frequency trade data can perhaps shed more light on the dynamics of the trading between institutions and other investors in these stocks, including direct measures of the price impacts of each trade and an examination of whether institutions profit from their herding.

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 concludes the paper.

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 collect 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, in contrast to Lakonishok, Shleifer, and Vishny (1992) and Kraus and Stoll (1972a). 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. 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 each quarter. These benchmark portfolios are formed 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. These ratios are also updated each June, with the fiscal year-end book value of equity from the preceding calendar year and the market value of the equity from the prior December. Finally, we sort stocks in each size/book-to-market group

[6] We discuss the results using the share-based measure, as well as using the change in the percentage of institutional ownership, in section 2.6. 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.

into quintiles each quarter based on their prior 12-month return, skipping one month. For example, in the third quarter (ending September), we sort using the 12-month period concluding at the end of August. We calculate the equally weighted returns for each of the 125 benchmark portfolios over the subsequent quarter, and subtract each specific stock's corresponding benchmark return from the stock's quarterly return to arrive at an abnormal return over the subsequent quarter. 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 returns 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. Before examining the return 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
Extreme Buy Herd	30 (22)	0.75 (0.73)	5.42% (3.15%)
Extreme Sell Herd	58 (27)	0.32 (0.34)	−3.53% (−1.64%)

We see that stocks in the top decile of $HERD_t$ have a mean number of 30 institutions changing their net holdings that 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 extreme 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%.

2.2. Portfolio Evidence

To examine how herding relates to future stock returns, we calculate the mean quarterly abnormal returns over various event-time windows for the stocks with the highest values of $HERD$ (extreme buy herd) and the lowest values of $HERD$ (extreme sell-herd), as well as the other deciles. We calculate abnormal returns for these equally weighted portfolios in calendar time and then obtain standard errors from the resulting time series. We first average abnormal returns across all available event-quarter portfolios in each calendar quarter. For example, with the event window $[t+5, t+8]$, there are four extreme-buy-herd portfolios 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.

Table 1 reports the mean abnormal returns for the decile portfolios over quarters $[t+1, t+4]$, $[t+5, t+8]$, and $[t+1, t+8]$. More importantly, Table 1 also gives the abnormal returns for the (10-1) portfolio, constructed as a long position in the extreme buy-herd stocks and a short position in the extreme sell-herd stocks. This portfolio provides the first test of the relation between herding and returns. We see that this portfolio generates a DGTW abnormal return of negative 0.97%

per quarter (with a p-value less than 1%) across quarters 5 to 8. Hence, herding results in return reversal in the second year after the herding.

We also show market-adjusted returns as a robustness check, given potential concerns about misspecification of expected returns. The return on the value-weighted Market index from CRSP is subtracted from a given portfolio's return in the corresponding calendar quarter. For the (10-1) portfolio, this measure is equivalent to the difference in raw returns across portfolios 10 and 1. Using raw returns, we find a strong year 2 reversal as well. In addition, the year 2 abnormal returns are generally decreasing across portfolios 1 to 10 using either measure in Table 1, further indicating that herding is negatively related to year 2 returns.

Table 1 also shows that abnormal returns are unrelated to herding over the first four quarters. Note that the absence of return continuation in year 1 contrasts with the findings of Wermers (1999) and Sias (2004). However, this is simply due to subperiod variation in the relation between herding and shorter run returns. Over 1980 to 1992, which is comparable to their sample periods, we see return continuation for a short period following the herding. For the more recent years 1993 to 2005, however, we see no evidence of any return continuation; Brown, Wei, and Wermers (2008) note this as well in their examination of mutual fund herding. In contrast to the sensitivity of shorter run return continuation to the sample period examined, longer run reversals are robust across subperiods. We expand on these points and reconcile our findings with the prior literature in greater detail in section A.2 of the Appendix.[7]

[7] Wermers (1999) examines herding in mutual funds while we, along with Sias (2004), examine herding in 13F institutions. The 13F data are holdings data for all institutions with at least $100 million under management and for positions of at least $200,000 or 10,000 shares. The 13F data might provide an advantage in a study of herding as these 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

2.3. Cross-Sectional Regressions

We employ cross-sectional regressions to further examine the relation between herding and future abnormal returns. Regressions provide a more rigorous test as information from the full cross section of stocks is brought to bear, not just those in the extremes of herding. Regressions also easily allow for more control variables to be considered. In particular, 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 return only controls for prior 12-month return, we expect to see large abnormal returns over shorter horizons. In fact, we find that the DGTW-adjusted returns for the (10-1) portfolio in quarters $-2, -1,$ and 0 are 11%, 15%, and 18% respectively. Given that various horizons of shorter term lagged returns are known to each display marginal effects on future returns (Gutierrez and Kelley (2008)), and that such shorter horizon returns tend to persist for several quarters and then reverse over longer horizons (Jegadeesh and Titman (1993)), it is important to control for these other lagged returns in our examinations of future returns.

Each quarter we regress stock returns on lagged values of $HERD$ and control variables. The respective t-statistics are calculated by dividing the mean of the quarterly time series of each coefficient by its time-series standard error. To examine multiple-quarter windows of future returns, for example quarters 5 through 8, we pool the time series of coefficients across all single-quarter analyses. That is,

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was required only semiannually until 2004. Nevertheless, as shown in the Appendix, we can qualitatively reproduce Wermers' (1999) mutual fund findings with the 13F data.

to explain abnormal returns in the quarter ending September 1988, we consider four estimates of the coefficient on $HERD$ corresponding to four separate and rolling regressions, one using $HERD$ in June of 1987 (5 quarters back), another using $HERD$ 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. Although not shown in our tables, the use of the efficient-weighting procedure of Ferson and Harvey (1999) to account for heteroskedasticity does not alter our main findings.

We consider three regression specifications to provide robustness. In the first, we regress raw returns in quarters $t + k$ on $HERD_t$. In the second specification, which we consider to be our main model, we regress future raw returns on $HERD_t$, r_t, $r_{t-2,t-1}$, the log of the book-to-market ratio of equity (BM), and the log of size, where r_t is the raw return in the same quarter as the herding measure, $r_{t-2,t-1}$ is the raw return over quarters $[t-2, t-1]$, and BM and size are as defined in the DGTW procedure in section 1.2. In the third specification, we regress future DGTW-adjusted returns on r_t and $r_{t-2,t-1}$.[8]

Table 2 provides the regression results. Herding is negatively related to returns in quarters 5 to 8, with the absolute value of the t-statistics greater than 2.6 across the spectrum of regression specifications. In short, return reversal in the second year is quite robust. To facilitate interpretation of the regressions, recall that the mean difference in $HERD$ across stocks with extreme buy herds and stocks with extreme sell herds is 0.43 [=0.75-0.32]. The regressions then predict a

[8]Controlling for prior one year return ($r_{t-4,t-1}$) and prior three year return ($r_{t-12,t-1}$) as well in these models do not alter the main findings. The inclusion of the three-year return establishes that the well-known longer run reversals found by De Bondt and Thaler (1985) are not driving our results.

return reversal varying from $-1.77\%[= -4.11(0.43)]$ to -0.68% per quarter across quarters 5 to 8.[9]

2.4. New perspective

The current view is that institutional herding contributes to price discovery in the stock market. Wermers (1999) and Sias (2004) find evidence of institutional herds moving stock prices, but importantly, no evidence of future return reversal. As noted earlier (and in the Appendix), the return reversal in the second year after the herding is robust and even evident in similar sample periods to those examined by Wermers and Sias. In short, the evidence indicating that herding results in excessive stock movement has existed as far back as 1980. This longer run return reversal, detected in Tables 1 and 2, alters the current perception that herding solely helps impound information into prices. Buy herding seems to spark an excessive price increase, and sell herding an excessive price decrease.

Are prices excessive at the end of the herding quarter, or after subsequent quarters? To address this, we note that the longer run return reversal following a herd actually dominates any shorter run return continuation (which is limited to the early subperiod). We can see this by returning to Table 2. Across quarters 1 to 8, the coefficients on $HERD_t$ are statistically negative in all three cases, with the absolute values of the t-statistics varying from 2.58 to 2.95. This reversal across quarters 1 to 8 is also evident using the (10-1) portfolio test in Table 1. The fact that the return reversal is the dominant effect in the post-herding period

[9]As a side note, Table 2 also reveals that the effects of lagged returns are not fully controlled for using the DGTW matching method; r_t is positively related to abnormal returns in quarters 1 to 4. Hence, the DGTW procedure does not fully control for return momentum, despite the claims made in a great many studies. This is not surprising given that applications of the DGTW procedure only control for a single lagged return horizon while many lagged return horizons display marginal momentum effects (Gutierrez and Kelley (2008)).

suggests that herding pushes prices beyond their intrinsic levels in the herding quarter.[10]

While our findings suggest that herding *over a quarter* pushes prices too far, note however, that we cannot distinguish between the direct price impact of the institutional herd of trades, the intraquarterly return chasing behavior of the institutions, and the intraquarter return forecasting ability of the institutions. In the next section, we provide evidence suggesting that the price impacts of the trades drive our findings.

2.5. Buy/Sell Asymmetry in Longer Run Reversal

Studies of daily and weekly institutional trading find that the typical trade pushes prices (Kraus and Stoll (1972b), Chan and Lakonishok (1995), Kaniel, Saar, and Titman (2008), and Campbell, Ramadorai, and Schwartz (2009)). Our lower frequency finding suggests that a herd of institutional trades over a quarter pushes prices so far that a correction over the subsequent two years is warranted. The high-frequency studies reveal a second phenomenon as well: Institutional buys have a greater (permanent) impact on prices than do institutional sells. The long-standing interpretation of this finding is that institutional buys are more informative than sells.[11] Chiyachantana, Jain, Jiang, and Wood (2004) provide a recent insight into this asymmetry by showing that it varies over time. Specifically, they find that the asymmetry in price impacts changes with stock market conditions. Buys have greater price impact in up markets, while sells have greater

[10]Herding displays no relation to abnormal returns over quarters 9 to 12.

[11]Saar (2001) provides a model of institutional trading in which such an asymmetry can arise. He shows that institutional buys generally should be more informative about stock valuation than institutional sells, and so should have greater price impact, when institutions (i) conduct research, (ii) do not borrow money, (iii) do not concentrate their holdings in just a few stocks, and (iv) do not short sell stocks. Also, he predicts that the asymmetry in price impacts can change, and even become negative when recent abnormal returns are sufficiently high.

price impact in down markets. This finding suggests that dealers require greater compensation for buy orders when stock prices are rising market wide and greater compensation for sell orders when stock prices are falling market wide.

These prior findings regarding an asymmetry in the price impacts of institutional buy and sell trades offer two predictions for our quarterly examination of institutional herding. One, a herd of buys should drive prices upward on average more than a herd of sells drives prices downward.

In fact, the high-frequency literature finds that institutional sells on average have little permanent impact on prices (large reversal of a sell's price pressure after a few days), suggesting that a herd of sells over a given quarter might not produce much, if any, accumulated decrease in prices. Two, the price impact of a herd of buys should be greater than that for a herd of sells when the herding occurs in an up market, but the price impact of a herd of sells should be greater when the herding occurs in a down market.

Without trade-by-trade data, the way for us to test these predictions is to examine abnormal returns (reversal) following the herding. Returning briefly to Table 1, we can see portfolio evidence consistent with the first prediction. Specifically, the stocks with extreme sell herds do not display an abnormal DGTW-adjusted return in quarters 5 to 8, while the buy herd displays a robust negative abnormal return using both measures in Table 1.

To investigate a potential asymmetry in the return reversal more rigorously, we employ our cross-sectional regression procedure and define two new measures of herding,

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

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

where $\overline{HERD_t}$ is the cross-sectional median of $HERD$ in quarter t. Similar adjustments are commonly used in the literature to define buy and sell herds. Employed as regressors, the two above measures estimate the slopes of the relations between herding and future returns across buy and sell herds respectively. We allow for the intercepts to differ across buy and sell herds by adding a dummy variable, DUM_t^{Buy}, set to one when $BuyHERD$ is not equal to zero.

Table 3 reports the results of the regressions isolating buy and sell herds. We focus our discussion on returns in the second year as this is the horizon over which the reversal, the presumed correction, occurs. The first year only serves to add noise, making an examination across quarters 1 to 8 less useful.[12] $BuyHERD_t$ is negatively related to abnormal returns over quarters 5 to 8 in each of the three specifications, with t-statistics ranging in absolute value from 3.41 to 4.16. In contrast, $SellHERD_t$ displays no statistical relation to future abnormal returns (not even in any of the individual quarters 1 through 8, untabulated). The point estimates on $SellHERD$ in some specifications are sizable though, suggesting a lack of power to detect reversal; but this is not always the case. In short, stocks with buy herds robustly reverse in the longer run while stocks with sell herds do not. This asymmetry is consistent with the unconditional price impact findings of the high-frequency studies of institutional trades.

To investigate the price pressure hypothesis further, we test the second prediction from the high-frequency literature. The findings of Chiyachantana, Jain,

[12]As evident in section A.2 of the Appendix, not only are there sizable changes from the early to late subperiods in abnormal returns over quarters 1 to 4, but the standard errors in each subperiod are larger in the first year than the second year.

Jiang, and Wood (2004) imply that, if price impact does drive our longer run return reversal, then the reversal should vary with market conditions — stocks with buy herds should reverse more in up markets, and stocks with sell herds should reverse more in down markets.

As a first test, we separate each herding quarter into high, medium, and low states with "High" defined to be the quarters when the return on the value-weighted CRSP index is above the 90^{th} percentile of returns in all quarters in the sample period, "Low" defined to be the quarters when the Market return is below the 10^{th} percentile, and "Medium" defined as the remaining quarters. We then calculate the mean coefficients on $BuyHERD$ and $SellHERD$ across quarters 5 to 8 from the regressions in Table 3. This measures the sensitivity of returns in quarters 5 to 8 to buy and sell herding within each of the three market states. For brevity, we consider only the first and second models from Table 3, labeled "no controls" and "controls" respectively; the third model, with DGTW-adjusted returns as the dependent variable, produces similar findings.

Table 4 gives the relations between returns in quarters 5 to 8 and buy and sell herding, respectively. The findings in Table 4 are consistent with Table 3 in that sell herds are not statistically related to longer run return reversal in the average ("Med") state, while buys herds are. More importantly though, we find the *opposite* asymmetry in bad times — a sell herd in a down market produces a robust return reversal, while a buy herd does not. This is shown by the negative mean coefficient on $SellHERD$ in the Low state in both specifications of Table 4, and an insignificant coefficient on $BuyHERD$.

As a second test of whether the relations between longer-run return reversal and buy and sell herds vary with market conditions, we regress the coefficients on $BuyHERD$ from Table 3 on the market's returns in the herding quarter. We do the same for the coefficients on $SellHERD$. Essentially, we examine whether quarterly variation in longer run reversal depends on the market's return in the herding quarter. Table 5 reports the results and confirms that market conditions affect buy and sell herds differently. In fact, the asymmetry in these relations is perhaps even easier to see in this way. The sell herd coefficients over quarters 5 to 8 are *increasing* in the market's return, meaning that the returns of stocks with sell herds reverse less as the market's return increases. In contrast, the buy herd coefficients are, if anything, *decreasing* in the market's return, meaning that the returns of stocks with buy herds reverse more as the market's return increases.

A potential concern with this evidence, or an alternative interpretation, is that the relations in Tables 4 and 5 are due to a cyclical risk premium. Specifically, we know that stocks with greater buy herding tend to have higher returns in the herding quarter. In up markets, these stocks will tend to have higher betas. If market returns this quarter are negatively serially correlated with market returns in quarters 5 to 8, then a cyclical risk premium (not captured by any of the controls we are already employing) might explain our results. A similar cyclical story might apply for the stocks with sell herds in down markets. To allay this concern, we note that the market's return in the herding quarter has zero correlation with its return in quarters 5 through 8 ($\rho = -0.003$ with a t-statistic of -0.06).

Consistent with the literature on the price impacts of institutional trades, the relation between buy and sell herds and future returns is asymmetric and dependent on the market's condition during the herding quarter. In short, sell herds in down markets seem to drive prices too low, and buy herds in up markets seem to drive prices too high.

2.6. Robustness Considerations

In the next subsections, we further consider the robustness of the longer run negative relation between institutional herding and future stock returns. First, we examine whether this relation is confined only to small stocks; then we consider two alternative measures of herding.

2.6.1. Small and Large Stocks

We form two subsamples of stocks each June, stocks with market capitalizations below the 10^{th} percentile of NYSE stocks (the "smallest") and the remaining stocks. We then estimate regressions as in Table 2. Table 6 shows the results. While the second year reversal in returns is much stronger in the smallest stocks, in terms of point estimates, the reversal is evident in the larger ("other") stocks as well. The coefficient on $HERD_t$ in quarters 5 to 8 for the larger stocks is statistically negative at the 5% level with a coefficient that remains sizable compared to those in Table 2. For brevity we do not report the results for the other two regression models (as in Table 2); the findings are similar with these models. In short, return reversal following a herding is not isolated to small stocks.

2.6.2. 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 the finding of a negative relation between herding and future returns is obtained using (i) an analogous share-based measure of herding and (ii) 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.[13]

The first two columns of Table 7 examine the share-based measure and its relation to future abnormal returns (as done in Table 2). We see a strong negative coefficient on $HERD_t^{Shrs}$ in quarters 5 to 8. In the last two columns of Table 7, we compete the original measure, $HERD_t$, with the share-based one. Longer run reversal following a buy herd is better captured with the earlier measure, as the share-based measure of buy herding no longer displays any significance.

Note too that the share-based measure is statistically negatively related to returns in quarters 1 to 4, which is a stronger finding than for $HERD_t$, which is insignificant in the first year (Table 2 as well) . This shorter-run finding for the share-based measure, however, dissipates when the control variables are removed.

The findings for ΔIO_t are very similar. The first two columns of Table 8 examine changes in institutional ownership without considering $HERD_t$. This alternative measure also predicts reversals in future returns following herding, in both the first and second years. But again, the first year reversal is sensitive to the model considered (untabulated). The upshot from Table 8 is that ΔIO robustly

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

predicts return reversal in the second year, but this explanatory power of ΔIO is dominated by that of the original measure, $HERD$.[14]

3. Conclusion

In contrast to the prior literature on institutional herding, we find that herding predicts future reversal in returns. This reversal occurs in the second year after the herding, which is a longer window than is previously examined. These longer run reversals indicate that herding pushes prices beyond their intrinsic levels, changing the extant view of the effects of herding. In fact, the return reversal dominates any shorter run return continuation that exists in the early portion of the sample period. Our findings suggest that herding results in price movements that are excessive.

This notion that institutional herding pushes prices too far is also consistent with the high-frequency literature on the price impact of institutional trades. That literature finds that (i) the typical institutional trade pushes prices and (ii) stock market conditions drive the well-documented asymmetry between the price impacts of institutional buys and sells. We find that market conditions in the herding quarter drive a similar buy/sell asymmetry in longer run return reversal. That is, a herd of buys seems to push prices too high in an up market, and a herd of sells seems to push prices too low in a down market.

The evidence we detect of institutions' having deleterious effects on stock prices (when they herd together to buy or to sell) echoes the messages of recent studies examining institutions in other settings. For example, Dasgupta, Prat,

[14] Dasgupta, Prat, and Verardo (2008) 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.

and Verardo (2008), 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, perhaps with higher frequency data, to identify and isolate why institutions trade as they do in these various circumstances is warranted.

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.[15]

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

[15] 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.

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 assume that a stock entry occurred in quarter t; instead, we set CHG_t to missing.[16] 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.[17]

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.

[16]See footnote 15.

[17]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%.

A.2. Reconciliation of Shorter Run Findings with Prior Studies

Here we reconcile our shorter run findings with the prior literature. While we detect little evidence of return continuation across quarters 1 to 4 in Table 1, Wermers (1999) and Sias (2004) find return continuations across the first year after the herding. Since Wermers reports more detailed results, as he gives abnormal returns for each quarter and for buy-herd and sell-herd portfolios separately, we focus our comparison on his study.

Although Wermers examines mutual fund herding, we find that 13F herding produces similar results to his over a comparable sample period. Note too that we use size-adjusted returns in this section as Wermers does. We split our sample into two subperiods, 1980 to 1992 and 1993 to 2005, to facilitate the comparison; Wermers examines mutual fund herding from 1975 to 1994.[18]

Panel A of Table A reports abnormal returns in the early subperiod for the extreme sell-herd and extreme buy-herd portfolios and the difference between the two. Our findings are similar to Wermers' (1999) Table VI. We find that stocks with extreme sell herds experience negative abnormal returns for two quarters. Stocks with extreme buy herds experience positive abnormal returns for one quarter. In addition, the difference between the extreme buy-herd and extreme sell-herd portfolios shows strong return continuation following a herd in the early subperiod that lasts for two quarters. Finally, Wermers finds evidence of a return reversal on the buy side in quarter 4 as we do. In sum, we can qualitatively reproduce the set of Wermers' findings.

[18]There are other procedural differences between our analysis and Wermers' (1999). He employs size deciles in his construction of abnormal returns; we employ quintiles. He separates stocks into five buy quintiles and five sell quintiles; we simply sort stocks into deciles based on $HERD_t$.

Panel B gives abnormal returns for the late subperiod and shows that shorter run return continuation after the herding does not exist in recent years. Brown, Wei, and Wermers (2008) make this point using mutual fund herding. However, the (10-1) portfolio displays a negative abnormal return in quarters 5 to 8 in both Panel A and Panel B. Therefore, in contrast to the subperiod variation in the shorter run return continuation, the longer run return reversal that is the focus of our study persists across the early and late subperiods.

Table A
Abnormal Returns of Stocks with Extreme Herds: Subperiods

Each quarter of 1980 to 2005, we sort stocks into deciles based on $HERD_t$. Stocks with less than ten institutions making net changes in holdings during quarter t are excluded. Stocks in the bottom decile (portfolio 1, extreme sell herd) and top decile (portfolio 10, extreme buy herd) are identified. Each stock's abnormal quarterly return is determined by subtracting the return of the matching size quintile. The size portfolios are the same as those used in the DGTW procedure described in section 1.2. The abnormal returns for the portfolios below are calculated over various future windows using the calendar-time procedure described in section 2.2. Quarterly abnormal returns are in percent.

Portfolio	Qtr 1	Qtr 2	Qtr 3	Qtr 4	Qtrs 1 − 4	Qtrs 5 − 8
			Panel A: 1980 to 1992			
1	−1.00	−0.94	−0.30	0.08	−0.58	0.41
	(2.28)	(2.49)	(0.70)	(0.19)	(1.59)	(1.24)
10	1.43	0.35	−0.09	−0.78	0.32	−0.69
	(3.52)	(0.83)	(0.28)	(2.78)	(1.03)	(3.14)
(10-1)	2.43	1.30	0.21	−0.86	0.90	−1.11
	(3.47)	(1.79)	(0.34)	(1.33)	(1.49)	(2.28)
			Panel B: 1993 to 2005			
1	−0.17	0.80	0.92	1.50	0.69	1.14
	(0.15)	(0.76)	(1.01)	(2.01)	(0.78)	(2.28)
10	0.66	−0.51	−0.81	−1.57	−0.55	−0.92
	(0.90)	(0.90)	(1.56)	(3.14)	(1.16)	(2.54)
(10-1)	0.83	−1.31	−1.73	−3.07	−1.24	−2.06
	(0.50)	(0.92)	(1.41)	(2.90)	(1.04)	(2.93)

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Table 1
Abnormal Returns of Stocks across Herd Deciles
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. The abnormal returns of stocks in each decile are equally weighted using calendar-time portfolios. Quarterly abnormal returns are in percent. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	DGTW-Adjusted Return			Market-Adjusted Return		
	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 1 − 8	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 1 − 8
1 (Extreme Sell Herd)	−0.19	0.30	0.02	0.37	1.02***	0.61
2	0.06	0.19	0.12	0.15	0.51	0.26
3	0.10	0.16	0.12	−0.01	0.40	0.13
4	0.00	0.13	0.07	−0.12	0.23	0.02
5	−0.11	−0.03	−0.07	−0.30	0.03	−0.17
6	−0.05	0.13	0.03	−0.24	0.17	−0.08
7	−0.14	0.04	−0.05	−0.36	0.04	−0.20
8	−0.12	−0.19	−0.14	−0.29	−0.15	−0.25
9	−0.09	−0.19	−0.12	−0.11	−0.31	−0.20
10 (Extreme Buy Herd)	−0.23	−0.67***	−0.41**	−0.16	−0.90**	−0.47
(10 − 1)	−0.04	−0.97***	−0.43*	−0.53	−1.92***	−1.08**

Table 2
Regressions of Future Stock Returns on Herding

Each quarter from 1980 to 2005, we regress various windows of future quarterly stock returns on $HERD_t$ and control variables. $HERD_t$ is 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. Raw returns over quarter t and over quarters $[t-2, t-1]$ are denoted r_t and $r_{t-2,t-1}$ respectively. $Size$ is the market capitalization of the stock at the end of the most recent June. BM is the ratio of the book value of equity from the fiscal year-end in the prior calendar year to the market value of the equity from the prior December, used to explain returns in the subsequent September and next three quarters. The absolute values of the t-statistics are in parentheses. The standard errors are clustered by calendar quarter. Coefficient estimates are multiplied by 100.

	Raw Ret.			Raw Ret.			DGTW-Adj. Ret.		
	Qtrs $1-4$	Qtrs $5-8$	Qtrs $1-8$	Qtrs $1-4$	Qtrs $5-8$	Qtrs $1-8$	Qtrs $1-4$	Qtrs $5-8$	Qtrs $1-8$
$HERD_t$	−1.68	−4.11	−2.87	−1.43	−2.09	−1.75	−0.74	−1.59	−1.16
	(1.18)	(3.72)	(2.95)	(1.87)	(2.68)	(2.69)	(1.29)	(2.93)	(2.58)
r_t				2.50	−1.13	0.72	0.86	−0.25	0.32
				(3.40)	(1.92)	(1.29)	(3.05)	(0.66)	(1.31)
$r_{t-2,t-1}$				0.75	−1.14	−0.18	−0.02	−0.29	−0.15
				(1.27)	(2.41)	(0.40)	(0.08)	(0.89)	(0.74)
$ln(Size)$				−0.13	−0.06	−0.09			
				(0.68)	(0.30)	(0.50)			
$ln(BM)$				0.76	0.59	0.68			
				(2.36)	(1.76)	(2.09)			
Intercept	0.78	2.27	1.51	2.65	2.45	2.55	0.25	0.87	0.56
	(0.92)	(3.72)	(2.53)	(1.18)	(1.02)	(1.12)	(0.84)	(3.16)	(2.46)
Avg N	2464	2265	2366	2415	2223	2321	2459	2257	2360
Avg R^2	0.01	0.00	0.00	0.05	0.04	0.05	0.01	0.01	0.00

Table 3
Regressions of Future Stock Returns on Buy and Sell Herding

Each quarter from 1980 to 2005, we regress various windows of future quarterly stock returns on $BuyHERD_t$, $SellHERD_t$, and control variables. $BuyHERD_t$ 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. 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. $Size$ is the market capitalization of the stock at the end of the most recent June. BM is the ratio of the book value of equity from the fiscal year-end in the prior calendar year to the market value of the equity from the prior December, used to explain returns in the subsequent September and next three quarters. 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. The absolute values of the t-statistics are in parentheses. The standard errors are clustered by calendar quarter. Coefficient estimates are multiplied by 100.

	Raw Ret.			Raw Ret.			DGTW-Adj. Ret.		
	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 1 − 8	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 1 − 8	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 1 − 8
$BuyHERD_t$	0.40	−4.96	−2.22	−0.75	−2.95	−1.83	−0.97	−2.93	−1.94
	(0.21)	(3.41)	(1.45)	(0.89)	(3.61)	(2.67)	(1.46)	(4.16)	(3.37)
$SellHERD_t$	−2.79	−4.10	−3.44	−1.87	−1.76	−1.82	0.11	−0.62	−0.25
	(0.89)	(1.55)	(1.26)	(1.02)	(1.21)	(1.21)	(0.09)	(0.62)	(0.27)
r_t				2.51	−1.12	0.73	0.87	−0.23	0.33
				(3.41)	(1.91)	(1.30)	(3.05)	(0.61)	(1.35)
$r_{t-2,t-1}$				0.76	−1.15	−0.18	−0.01	−0.30	−0.15
				(1.29)	(2.43)	(0.40)	(0.06)	(0.91)	(0.75)
$ln(Size)$				−0.12	−0.07	−0.09			
				(0.66)	(0.35)	(0.51)			
$ln(BM)$				0.76	0.59	0.67			
				(2.39)	(1.77)	2.11			
Intercept	1.26	2.29	1.77	2.74	2.40	2.57	−0.11	0.43	0.15
	(0.94)	(2.17)	(1.62)	(1.12)	(0.95)	(1.06)	(0.19)	(0.90)	(0.37)
DUM_t^{Buy}	−1.72	0.52	−0.62	−0.65	0.69	0.01	0.51	1.29	0.89
	(0.82)	(0.30)	(0.33)	(0.56)	(0.79)	(0.01)	(0.70)	(2.09)	(1.56)
Avg N	2464	2265	2367	2415	2223	2321	2459	2257	2360
Avg R^2	0.01	0.01	0.01	0.06	0.04	0.05	0.01	0.01	0.01

Table 4
Time-Series Variation in Relation between Herding and Returns over Quarters 5 to 8: High, Medium, and Low Market States

The mean of the coefficients on $BuyHERD_t$ (and on $SellHERD_t$) from quarters 5 to 8 in the regressions of Table 3 are reported in each of three states: High, Med, and Low. "High" is when the return on the value-weighted CRSP index from quarter t is above the 90^{th} percentile of the quarterly returns for the Market across the sample period; "Low" is when the Market's return is below the 10^{th} percentile in the herding quarter; and "Med" are the remaining quarters. The coefficients from the first model of Table 3 are labeled "No Controls," and those from the second model are labeled "Controls". The coefficients are multiplied by 100. The absolute value of the t-statistic is in parentheses. Standard errors are clustered by calendar quarter.

	No Controls			Controls		
	High	Med	Low	High	Med	Low
Buy Herd	−8.23	−5.18	0.10	−4.48	−2.98	−1.19
	(3.11)	(3.35)	(0.06)	(2.17)	(3.74)	(0.39)
Sell Herd	0.75	−3.28	−15.40	1.19	−1.08	−10.00
	(0.19)	(1.32)	(2.47)	(0.49)	(0.77)	(2.72)

Table 5
Time-Series Variation in Relation between Herding and Returns over Quarters 5 to 8: Regression on Market Return

The coefficients on $BuyHERD_t$ (and on $SellHERD_t$) from quarters 5 to 8 in the regressions of Table 3 are regressed on the returns of the value-weighted CRSP index from quarter t. The coefficients from the second-stage regression are reported below. The coefficients corresponding to the first model of Table 3 are labeled "No Controls," and those to the second model are labeled "Controls". The absolute value of the t-statistic is in parentheses. Standard errors are clustered by calendar quarter.

	No Controls	Controls
Buy	−0.174	−0.091
	(2.64)	(1.05)
Sell	0.357	0.298
	(2.26)	(2.84)

Table 6
Regressions of Future Abnormal Stock Returns on Herding within Smallest and Other Stocks

We follow the same procedure as Table 2 but estimate regressions within two subsets of stocks, the smallest and the others. The smallest stocks are those with market capitalizations less than that of the $10th$ percentile across NYSE stocks in the most recent June, before the herding quarter. Other 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.

	Smallest Stocks			Other Stocks		
	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 1 − 8	Qtrs 1 − 4	Qtrs 5 − 8	Qtrs 1 − 8
$HERD_t$	2.98	-6.48	-1.65	-1.10	-1.67	-1.38
	(1.20)	(2.60)	(0.96)	(1.52)	(2.32)	(2.34)
r_t	3.49	-0.72	1.43	2.49	-0.73	0.91
	(1.18)	(0.12)	(0.43)	(2.92)	(1.10)	(1.38)
$r_{t-2,t-1}$	0.90	-1.44	-0.25	0.93	-1.03	-0.03
	(1.44)	(2.00)	(0.50)	(1.42)	(1.94)	(0.06)
$ln(Size)$	1.77	-0.50	0.66	-0.10	-0.08	-0.09
	(1.81)	(0.43)	(0.84)	(0.58)	(0.46)	(0.53)
$ln(BM)$	0.06	0.56	0.31	0.74	0.56	0.65
	(0.14)	(1.28)	(0.77)	(2.37)	(1.69)	(2.06)
Intercept	-21.54	10.81	-5.69	2.00	2.50	2.24
	(1.92)	(0.77)	(0.62)	(1.01)	(1.14)	(1.11)
Avg N	333	271	302	2082	1952	2018
Avg R^2	0.15	0.16	0.15	0.06	0.04	0.05

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

We follow the same procedure as Table 2 but consider a new measure, $HERD_t^{Shrs}$, which is the number of shares bought on net by institutions in quarter t divided by the number of shares traded on net by institutions. 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 1 – 4	Qtrs 5 – 8
$HERD_t^{Shrs}$	-0.89	-1.01	-0.56	-0.43
	(2.58)	(2.57)	(2.05)	(1.21)
$HERD_t$			-0.96	-1.76
			(1.25)	(2.24)
r_t	2.48	-1.19	2.54	-1.09
	(3.28)	(1.98)	(3.47)	(1.87)
$r_{t-2,t-1}$	0.72	-1.20	0.77	-1.13
	(1.17)	(2.45)	(1.30)	(2.39)
$ln(Size)$	-0.13	-0.04	-0.13	-0.06
	(0.71)	(0.20)	(0.69)	(0.30)
$ln(B/M)$	0.75	0.61	0.76	0.59
	(2.34)	(1.81)	(2.37)	(1.77)
Intercept	2.42	1.61	2.71	2.50
	(1.15)	(0.74)	(1.21)	(1.05)
Avg N	2415	2223	2415	2223
Avg R^2	0.05	0.04	0.05	0.04

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

We follow the same procedure as Table 2 but consider a new measure, ΔIO_t, which is the change in the percentage of outstanding shares held by institutions. 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 $1-4$	Qtrs $5-8$
ΔIO_t	-3.31	-3.16	-3.09	-1.55
	(2.70)	(2.80)	(2.74)	(1.36)
$HERD_t$			-0.87	-1.89
			(1.11)	(2.32)
r_t	2.54	-1.21	2.60	-1.08
	(3.29)	(1.93)	(3.52)	(1.82)
$r_{t-2,t-1}$	0.73	-1.20	0.79	-1.12
	(1.18)	(2.40)	(1.33)	(2.33)
$ln(Size)$	-0.14	-0.04	-0.13	-0.06
	(0.74)	(0.20)	(0.69)	(0.30)
$ln(B/M)$	0.75	0.61	0.75	0.60
	(2.34)	(1.82)	(2.35)	(1.78)
Intercept	2.01	1.08	2.38	2.35
	(1.00)	(0.53)	(1.05)	(0.97)
Avg N	2415	2223	2415	2223
Avg R^2	0.05	0.04	0.05	0.04