Herding Among Individual Investors

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Abstract

The conjecture that investor sentiment leads important groups of investors to act similarly and thereby affect prices is an important ingredient of models of noise trading and style investing. In contrast to Lakonishok et al. (1992), who find only weak evidence of herding among institutional investors and conjecture that retail investors will herd even less, we document that a sample of over 30,000 retail clients at a German broker exhibits a strong tendency to herd at daily and quarterly horizons. Furthermore, we find a negative correlation between returns and retail buying which is entirely due to negative returns triggering the execution of limit buy orders (and positive returns triggering the execution of limit sell orders). Once we confine our attention to market orders, the correlation between retail buying and returns turns positive, especially for stocks in which retail investors own a comparatively high fraction of the company. Our results further strengthen the case for a positive impact of individual investor sentiment on returns, as suggested by Ofek and Richardson (2003) and Dorn (2002).

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1 Introduction

The conjecture that investor sentiment leads important groups of investors to act similarly, that is, herd, and thereby affect prices is an important ingredient of models of noise trading and style investing (see, e.g., De Long et al. (1990), Lee et al. (1991), Shleifer (2000), and Barberis and Shleifer (2002)). Mainly because of data availability, previous empirical work on herding has focused on the trading behavior of institutional investors; institutions file their holdings data at quarterly or semi-annual intervals for inspection by the public. The empirical support for the conjecture that U.S. pension funds or U.S. mutual funds herd, however, is weak, and inferences about the relation between institutional trading and returns are complicated by the low frequency of observations (see, e.g, Lakonishok et al. (1992) (LSV), and Wermers (1999)).

This paper empirically revisits the question of herding, but focuses on a different subset of investors; a sample of 30,000 active retail clients at a German online broker for whom daily transaction records are available at the account level. Retail investors may be more prone to systematic biases than professional investors or simply face greater search and selection costs when making financial decisions, which could lead to greater herding among retail investors. Odean (1998), for example, documents that clients at a U.S. discount broker tend to sell their winners and hang on to their losers. For the same sample, Barber and Odean (2002) find that retail clients tend to buy attention-grabbing stocks, i.e., stocks that experience abnormally large price moves, trading volume, or media coverage.

The sample of German online brokerage clients indeed exhibits a strong tendency to herd in German stocks at different horizons. At a daily frequency, 59% of the retail clients change their holdings of an average stock in one direction and 41% in the opposite direction. At a quarterly frequency, 57% of the retail clients are on one side of the market in an average stock. In contrast, only 52% of the money managers in Lakonishok et al. (1992) are on one side of the market at a quarterly frequency. The paper documents similar levels of retail herding when the herding measures are calculated just considering market orders as opposed to considering both market orders and limit orders; in other words, the observed herding is not merely an artefact of, e.g., limit buy orders being systematically executed after price increases. Moreover, high levels of herding in a stock tend to occur during periods with active retail participation; the observed herding is not driven by observations with few traders, which also alleviates concerns that herding might be wrongly inferred in the presence of short-sale constraints (see Wylie (2002)).

These results contribute to an emerging literature that examines how financial decisions of individual investors aggregate. Barber et al. (2002), for example, draw random subsamples from a sample of U.S. discount brokerage investors and find that the sampled brokerage clients tend to be on the same side of the market in a given stock and month. For the same sample, Kumar (2002) documents that at a monthly frequency retail investors tend to co-move into stocks with similar attributes such as book-to-market ratios and firm size in response to good past performance. Our results show an economically and statistically significant magnitude of herding at a daily frequency, controlling for trading activity and limit order effects.

In an important second step, this paper - again benefitting from the high frequency with which trades and returns are observed - relates the herding tendencies of retail investors to abnormal stock returns. There is a negative correlation between the sampled investors' tendency to buy and abnormal stock returns which is entirely due to the execution of limit orders against price movements;[1] limit sales occur during price increases and limit purchases during price decreases. When only market orders are considered,

[1] Jackson (2003) also finds a negative correlation between returns and individual investors' buy pressure, with weekly data.

the correlation between retail buying and stock returns turns strongly positive, which illustrates the importance of accounting for different order attributes. For observations with a high retail investor participation and for stocks in which the sampled retail clients hold a disproportionately high fraction of the outstanding stock, the correlation between retail purchases and abnormal returns is strongly positive regardless of whether or not limit orders are considered. Intra-day momentum trading is unlikely to be the only explanation for the positive correlation between retail buying and returns since the correlation is similar, if not stronger, when the analysis is confined to those orders that have to be placed before 10am on a day to be executed on the same day. Moreover, there is some evidence for return reversals following days of intense retail buying. These results are consistent with retail buying pressure temporarily affecting prices.

The positive contemporaneous correlation between retail purchases and abnormal returns, particularly for observations where retail investors are relatively important market participants, is remarkable given previous research that documents a positive contemporaneous relation between abnormal returns and changes in *institutional* ownership at annual, quarterly, and daily horizons (see, e.g., Nofsinger and Sias (1999), Wermers (1999), and Griffin et al. (2003)). It is consistent, however, with the positive correlation between retail buying and open-to-close returns of initial public offerings (IPOs) on the day of the IPO, as documented by Dorn (2002).

The remainder of the paper proceeds as follows: Next is a description of the data. Section Three presents the results on retail investor herding. Section Four relates the investors' herding tendencies to abnormal returns, and Section Five concludes.

2 Data

The paper relies on complete daily transaction records between January 1, 1999 and May 31, 2000 for a sample of over 30,000 customers at a large German online broker; in principle, brokerage transaction records are available for each account from the account opening date until May 31, 2000 but certain asset attributes such as trading volume only become available through Datastream in January 1999. "Online broker" refers to the ability to process online orders; customers can also place their orders by telephone, fax, or in writing. The broker could be labelled as a "discount" broker because no investment advice is given. In principle, brokerage customers can trade all the bonds, stocks, and options listed on German exchanges, as well as all the mutual funds registered in Germany. The focus of this paper is on the transactions in domestic stocks. The typical record consists of a unique identification number, an account number, a transaction date, a buy/sell indicator, a limit order indicator that allows us to distinguish between limit orders and market orders, a stock exchange indicator that allows us to identify the exchange on which the order is placed, the type of asset traded (e.g., common stock), a security identification code, the number of shares traded, the gross transaction value, and the transaction fees.

The exchange indicator merits a remark. Depending on the stock, brokerage clients can choose where to place their order, e.g., in XETRA (the electronic limit order book), on the floor of the Frankfurt Stock Exchange, or in an Alternative Trading System. Only the Alternative Trading System allows intra-day trading during the sample period; orders placed on a stock exchange have to be received by 10am to be executed on the same day.

The paper relies on Datastream for daily stock return, stock trading volume, and market capitalization data.

3 Herding

Research on herding grew out of a concern that correlated behavior by investors may destabilize stock prizes, causing them to deviate from fundamental values, and increase volatility.

The earlier literature focused on institutional investors, both because they were widely perceived as having the largest impact on returns and because data on their holdings were traditionally more available through SEC filings. Since every sale corresponds to a buy of equal size, there cannot be herding on a market–wide level, but only for sub–groups of investors. This paper focuses on the sub–group of individuals.

Lakonishok et al. (1992) propose a measure of herding based on the buyers ratio, in their case, constructed as the number of portfolio managers in a given quarter buying a stock, divided by the total number of traders in that stock (buys plus sells):

$$br_{jt} = \frac{\sum_i B_{ijt}}{\sum_i (B_{ijt} + S_{ijt})} \tag{1}$$

where $B_{ijt} = 1$ if investor i was a net–buyer of stock j in period t. Similarly, $S_{ijt} = 1$ if she was a net–seller.

For liquidity and other reasons, one may observe buying or selling across all stocks for the subset of investors under consideration. A proper measure of herding should not classify high buyers ratios as herding if all investors buy on average. Subtracting the expected buyers ratio

$$E(br_{jt}) = \frac{\sum_j \sum_i B_{ijt}}{\sum_j \sum_i (B_{ijt} + S_{ijt})}$$

mitigates this bias.

To arrive at a proper test statistic that is zero under the null hypothesis that trading among investors is random and uncorrelated, Lakonishok et al. (1992) introduce an extra correction term and calculate their measure as

$$LSV_{ijt} = |br_{ijt} - E(br_{jt})| - E\,|br_{ijt} - E(br_{jt})|$$

The second term on the right hand side is the expected value of the herding measure under the null of no herding, i.e. if trades are random and uncorrelated.

Lakonishok et al. (1992) find only scant evidence for herding using this measure. For quarterly pension funds in the period 1985–1989, they find on average herding of 2.7%. This implies that assuming a $E(br_{jt})$, the average change, of 0.5, only 52.7% of managers were on the same side of the market.

Table 1 presents the same calculation for our sample, for both daily and quarterly horizons and for the sample with and without limit orders. For each, we compute the mean of the LSV measure conditional on the number of traders in any given stock–period (NT_{jt}).

Starting, for the sake of comparability, with the quarterly results, we find that among individual investors the average herding is drastically larger than what had been previously found. Across all observations with at least two traders[2] we find a value of 6.41%, more than twice LSV's result. There is also strong evidence that, for individual investors, a "larger herd is a stronger herd": for stock–quarters with at least ten active individuals, the LSV measure increases to 7.34%. In general, the number of traders NT_{jt} is a good proxy for trading intensity. Even controlling for firm size (not shown), herding rises monotonically with NT_{jt} which also alleviates concerns that herding might be wrongly inferred in the presence of short–sale constraints; Wylie (2002) finds that short–sale constraints induce a bias in the LSV measure especially in cases where only a small number of investors trade.

There is also some evidence that herding is not information but rather attention–

[2] It is hard to interpret observations with only one trader as herding.

based. We observe that, holding NT_{jt} constant, there is significantly more herding among foreign than domestic stocks. (not shown here)

Moving on to the daily frequency, the presence of herding becomes even more apparent. The LSV measure reaches its maximum of 8.74% for stock–days with at least ten traders. On a daily basis, given an expected buyers ratio of 0.5, almost 60% of trading brokerage customers find themselves on the same side of the market. Again, this finding increases with NT_{jt}. When we eliminate limit orders from the calculation (right hand side in Table 1), the values decline somewhat (to 7.25% for $NT_{jt} \geq 10$) but remain qualitatively unchanged.

4 Herding and returns

Ultimately, the impact on prices and returns drives the interest in herding. Documenting herding as we did in the previous section, begs the question of relevance. Correlated behavior among individual investors may exist, but does it influence prices? Individuals, being slower at observing relevant news, could react to information that is already incorporated in prices. Generally speaking, the brokerage customers may not be the marginal investors.

To measure the impact of herding on returns, we employ the simple buyers ratio defined in (1). We found similar results using other statistics of buy–pressure, such as the buy ratio, but stuck to br_{jt} for its simplicity and robustness to the behavior of a few wealthy individuals.

Overall, we find a negative correlation between the buyers ratio and excess returns on a daily frequency. Much of this negative correlation, however, is driven by limit orders. Including both limit orders and market orders by customers, the correlation is

-0.04, compared to 0.09 for only the market orders.[3] (See table 2.) The strong negative association of buyers ratio and returns is largely mechanical: On days with large positive returns, limit sell orders are executed, driving down the buyers ratio; on days with low returns, the analogue is true for limit buy orders.[4] This is especially true for stocks with little liquidity, where limit orders tend to be more popular.

The positive correlation, even correcting for average returns, is interesting in itself and suggestive of retail buy pressure. If retail buy pressure mattered, one should observe a stronger effect when retail trading intensity is high and for stocks that hold a special interest for our brokerage customers. High trading intensity, which we measure by the number of traders (NT_{jt}), dominates if investors trade for reasons other than liquidity or random private information. The market value share (MS_{jt}), i.e., the fraction of outstanding stock held by brokerage customers, proxies for their interest in the company.

For each stock–day, we sort all of the observations according to their market value share into three groups and create a set of dummy variables indicating the three groups. (D^1_{MS}–D^3_{MS}). Similarly, we group observations according to the number of traders: observations with only one trader, with two to four, and with five or more traders. (D^1_{NT}, D^2_{NT}, D^3_{NT}):

$$D^1_{NT} = \begin{cases} 1 \quad if \quad NT_{jt} = 1 \\ 0 \qquad otherwise \end{cases}$$

$$D^2_{NT} = \begin{cases} 1 \quad if \quad NT_{jt} \in [2, 4] \\ 0 \qquad otherwise \end{cases}$$

[3]Jackson (2003) finds a similar negative correlation for the weekly transactions of individual investors, but his data do not seem to include information on the order type.

[4]Stop–loss and stop–buy orders are uncommon.

$$D^3_{NT} = \begin{cases} 1 \quad if \quad NT_{jt} \geq 5 \\ 0 \qquad otherwise \end{cases}$$

Table 3 reviews the summary statistics for each of the nine NT/MS groups.

The differences in excess returns across groups are striking in their own right, varying from -0.123 percent per day in the medium market–value–share group with one trader, to 2.316 in the top market–value–share group with more than 4 traders. (See table 3, lower panel.) However, they do not capture the impact of buy pressure since buyers ratios are not held constant. To address this issue, we estimate multivariate OLS regressions.

The baseline regression interacts the buyers ratio with both sets of dummy variables, yielding nine parameter estimates for the sensitivity of returns to buy pressure:

$$r_{jt} = \alpha + \sum_{k=1}^{3}\sum_{l=1}^{3} \beta_{jt} br_{jt} D^k_{MS} D^l_{NT} + \epsilon_{jt} \tag{2}$$

The negative bias caused by the limit orders carries over to the regression results, but even here a fundamental positive relationship between buyers ratio and returns is discernible. The parameter estimates for (2) are shown in the first two columns of table 4. While most of the estimates are negative and significant, the estimate on br_{jt} turns positive for the groups that combine the top–two market value–share groups and the top trading intensity group. The inclusion of stock fixed effects (column 2) magnifies this result. Based on this estimate, a one–standard deviation increase of the buyers ratio for an observation that falls into the top tercile in terms of market value share while simultaneously being traded by at least 5 investors, increases the excess return by 0.48 percentage points.[5]

[5]For the standard deviation of the buyers ratio, see table 3; $0.232 * 2.069 = 0.48$

Repeating the regression without the limit–order observations reveals the full impact of the buyers ratio. (See columns 3 and 4 in table 4). Except for observations falling into the lowest market–value–share tercile, all of the coefficients are positive and statistically significant. Furthermore, within all of the groups the estimates are monotonically increasing, with the highest values in for the observations with a high market value share and many traders. To illustrate the magnitude, a one–standard deviation increase in the top group implies an abnormal return of almost 1.72 percentage points if we control for stock fixed effects (column 4).

One explanation for this result could be intraday positive feedback trading. If investors buy after observing a high return earlier in the day, we would observe an increase in the buyers ratio contemporaneously with high returns. Also, the buying would make it more likely that an observation is placed into the top market value share group.

To dispel this doubt, we further subdivide our sample, according to the channel used to place an order. Roughly speaking, investors have two choices. Either place an ordinary order, which has to be received before 10am to be forwarded to the floor on the same day, or trade directly via the Alternative Trading System. Only the latter allows for serious intraday momentum trading. The last two columns in table 4 show separate results for these two trading channels (termed "Ordinary Trades" and "Fast Trades"). Contrary to the assertion, the buy pressure effect is actually stronger for ordinary trades and weaker for trades executed through the Alternative Trading System.

Extensions

In table 5 we present a couple of extensions and robustness checks. All of the results are based on the market–order sample.

In table 3 one could observe that average returns are substantially higher for stock–days with a high number of traders or a high market value share. Concerned that the interacted buyers ratio might just pick up this absolute difference, we re–specified the regression to include the complete set of dummies in addition to the interaction. The result (in column 1) shows that the coefficients in the lower two market value share groups decrease somewhat, otherwise leaving the result unchanged.

In the next two columns, we first replace the stock–fixed effects with day fixed effects, then include one lag of the excess return in the regression. Neither change affects the size or direction of the coefficients in any substantial way.

The last column redefines the trading–intensity grouping. While the lowest group remains unchanged at $NT_{jt} = 1$, the medium/high cutoff changes to 8, placing only observations with $NT_{jt} \geq 9$ into the top group. This change increases the coefficient on buyers ratios for the highest NT_{jt}/MS_{jt} classification substantially, from 6.933 to 9.221.

Future returns

In the last table we take a look at the predictive power of the buyers ratio for returns up to three days into the future.

For the return on the next day, it seems that the effect of the previous day's buy pressure continues, albeit with a smaller magnitude. The coefficient on the buyers ratio in the top group of 1.186 predicts an abnormal return of 0.29 percentage points on the next trading day for a one–standard–deviation increase in the buyers ratio. The subsequent days see some return reversal. The same coefficient becomes -0.562, but is only marginally significant. There are more signs for reversal among the other coefficients, the pattern does not seem to be related to the NT/MS–grouping, however.

Including the same–day and/or lagged excess returns does not alter these findings. (Not shown.)

5 Conclusion

Contributing to the literature on herding which has focused on institutional investors, this study not only documents substantial herding among individual investors, but can also establishes a strong and stable positive relationship between retail buy pressure and excess returns at a daily frequency. On a technical note, the findings illustrate the importance of distinguishing between market orders and limit orders as the latter introduce a spurious negative correlation between retail buy pressure and returns.

Of course, the usual caveats apply. The brokerage customers may not be representative of the average individual investor, although the return results suggest so. Moreover, the German boom years of 1999-2000 don't exactly represent "normal times" for stock markets.

If the documented behavior generalizes across time and markets, one question emerges: how does this fit in with the accrued evidence of a positive correlation between returns and *institutional* buying? There is no evidence for German institutional investors, but if they exhibit this positive correlation as well, who takes the other side of the trade?

While this question remains open for now, some envisioned future research may shed some light. The documented behavior does not explain *why* individuals herd or, for that matter, trade at all. One extension, under work, explores persistence in retail buy pressure and its relation to past returns. There is some preliminary evidence that herding is even more pronounced in foreign stocks which may imply that attention plays an important role in triggering herding. Perhaps individual investors tend to react more to extreme news and information about foreign stocks needs to be more extreme to be reported, or foreign stock signals are more highly correlated because there is a smaller number of information outlets that individual investors pay attention to. In a second extension, studying the temporal aspects of herding and extending the return results to different time horizons has the potential of illuminating the causes of herding.

Another interesting extension explores the profitability of a trading strategy that consists of buying the stocks most aggressively bought and shorting the stocks most aggressively sold by retail investors. This should clarify if the arbitrage opportunities implied by the predictive power of retail buying are economically significant or merely a statistical artefact.

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Table 1: The LSV measure of Herding

This table summarizes the means of the herding measure by Lakonishok et al. (1992) (LSV), as described in the text. Rows show the measure, in percent, for different levels of trading activity, measured by the number of traders (NT_{jt}) by stock-day observation. On the left hand side of the table, we show the results for the entire sample (including both limit and market orders), on the right hand side only for market orders. The upper panel shows the result using data on the daily frequency, the lower on a quarterly frequency.
All estimates are significant on conventional significance levels.

	Market and Limit Orders		Only Market Orders	
Daily Data				
	Mean(LSV)	Observations	Mean(LSV)	Observations
NT_{jt} in [2,4]	3.12	23,816	3.02	15,303
$NT_{jt} >= 2$	4.71	37,389	4.43	21,985
$NT_{jt} >= 5$	6.74	13,573	6.27	6,682
$NT_{jt} >= 10$	8.74	5,060	7.25	2,242
Quarterly Data				
	Mean(LSV)	Observations	Mean(LSV)	Observations
NT_{jt} in [2,4]	3.50	697	1.22	618
$NT_{jt} >= 2$	6.41	3,138	4.82	2,379
$NT_{jt} >= 5$	7.06	2,441	5.52	1,761
$NT_{jt} >= 10$	7.34	1,907	5.93	1,332

Table 2: Summary Statistics

This table presents summary statistics, both for the complete sample (market and limit orders) and for the sample that only includes market orders.
Daily excess returns (r_{jt}) (from Datastream), were computed as the raw return, in percent, of stock j on day t minus the return on the DAX100 index.
The buyers ratio (br_{jt}) is the fraction of trades in stock j on day t that are buys.
The number of traders (NT_{tj}) is the number of trades in stock j on day t.
The market value share (MS_{jt}) (from Datastream) is the percentage of stock j held by all brokerage customers on day t.

Market and Limit orders

	Mean	Median	St.Dev.	Obs.	Correl. with r_{jt}
Excess return (r_{jt})	0.226	-0.227	5.084	63498	1.000
Buyers ratio (br_{jt})	0.481	0.500	0.410	63498	-0.044
Number of traders (NT_{tj})	3.791	2.000	9.105	63498	0.048
Market value share (MS_{jt})	0.155	0.100	0.280	63498	0.010

Only Market Orders

	Mean	Median	St.Dev.	Obs.	Correl. with r_{jt}
Excess return (r_{jt})	0.298	-0.218	5.408	41855	1.000
Buyers ratio (br_{jt})	0.449	0.500	0.421	41855	0.088
Number of traders (NT_{tj})	3.053	1.000	6.137	41855	0.071
Market value share (MS_{jt})	0.140	0.094	0.217	41855	0.013

Table 3: Summary Statistics by MV–share tercile and number–of–traders groups

This table summarizes excess returns (r_{jt}), the buyers ratio (br_{jt}), the standard deviation of the buyers ratio, the number of traders (NT_{jt}), and the market value share (MS_{jt}), separately by the market–value–share/number–of–trader groups defined in the text on page 9.

Market and Limit orders							
MS_{jt}	NT_{jt}	Mean(r_{jt})	Mean(br_{jt})	Std(br_{jt})	Mean(N_{jt})	Mean(MS_{jt})	Obs
Low	$=1$	0.023	0.458	0.498	1.000	0.029	9,728
	$\in[2,4]$	0.182	0.483	0.361	2.648	0.030	6,966
	≥ 5	0.375	0.495	0.283	12.455	0.030	4,387
Medium	$=1$	-0.092	0.467	0.499	1.000	0.102	9,186
	$\in[2,4]$	0.133	0.487	0.346	2.655	0.103	7,905
	≥ 5	1.166	0.531	0.252	10.785	0.105	4,512
High	$=1$	-0.065	0.459	0.498	1.000	0.344	9,557
	$\in[2,4]$	0.232	0.490	0.344	2.639	0.339	7,279
	≥ 5	1.171	0.522	0.232	12.642	0.311	3,978
Only Market Orders							
Mkt value share	#traders	Mean(r_{jt})	Mean(br_{jt})	Std(br_{jt})	Mean(N_{jt})	Mean(MS_{jt})	Obs
Low	$=1$	0.056	0.431	0.495	1.000	0.028	6,818
	$\in[2,4]$	0.198	0.480	0.358	2.632	0.028	4,701
	≥ 5	0.448	0.517	0.267	11.194	0.029	2,315
Medium	$=1$	-0.123	0.416	0.493	1.000	0.097	7,071
	$\in[2,4]$	0.421	0.465	0.351	2.624	0.098	5,049
	≥ 5	1.641	0.539	0.260	9.204	0.097	2,116
High	$=1$	-0.086	0.390	0.488	1.000	0.313	7,154
	$\in[2,4]$	0.340	0.462	0.350	2.592	0.276	4,725
	≥ 5	2.316	0.531	0.248	12.312	0.279	1,906

Table 4: Herding and Returns

This table reports the results of a regression of the excess return of stock j on day t (r_{jt}, in percent, computed over the DAX100) on the buyers ratio br_{jt}, with the buyers ratio fully interacted with dummy variables indicating market-value share terciles ($D^1_{MS} - D^3_{MS}$) and dummies indicating the number–of–traders groups (D^1_{NT} for observations with only one trader, D^2_{NT} with two to four traders, and D^3_{NT} five or more traders). The market value share MS_k was computed as the number of stocks held by all brokerage customers divided by the total outstanding stock, from Datastream.
"Ordinary trades" are all trades not placed through the Alternative Trading System, "Fast Trades" are transactions through the Alternative Trading System, which allows for immediate quotes and transactions. The number of observations for the two trading channels does not add to the total for "Only Market Orders" because on a given stock–day, there may be both "ordinary trades" and "fast trades".

	Dependent Variable: r_{jt}											
Sample:	Market and Limit Orders				Only Market Orders							
					All Market Orders				Ordinary Trades		Fast Trades	
	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se
$br_{jt} * D^1_{MS} * D^1_{NT}$	-0.692	(0.07)**	-0.884	(0.08)**	0.566	(0.11)**	0.196	(0.11)+	0.548	(0.12)**	-0.459	(0.16)**
$br_{jt} * D^1_{MS} * D^2_{NT}$	-0.748	(0.10)**	-0.835	(0.12)**	0.582	(0.17)**	0.302	(0.21)	0.972	(0.21)**	-0.407	(0.25)+
$br_{jt} * D^1_{MS} * D^3_{NT}$	-0.708	(0.21)**	-0.532	(0.29)+	0.976	(0.38)*	1.053	(0.54)+	1.512	(0.41)**	0.254	(0.58)
$br_{jt} * D^2_{MS} * D^1_{NT}$	-0.686	(0.08)**	-0.709	(0.08)**	0.663	(0.11)**	0.592	(0.12)**	1.244	(0.15)**	-0.402	(0.21)+
$br_{jt} * D^2_{MS} * D^2_{NT}$	-0.524	(0.13)**	-0.417	(0.14)**	1.724	(0.19)**	1.822	(0.22)**	2.412	(0.28)**	1.172	(0.27)**
$br_{jt} * D^2_{MS} * D^3_{NT}$	0.900	(0.35)*	1.434	(0.37)**	3.539	(0.71)**	4.341	(0.68)**	4.058	(0.84)**	3.903	(0.88)**
$br_{jt} * D^3_{MS} * D^1_{NT}$	-0.714	(0.07)**	-0.778	(0.09)**	0.953	(0.13)**	1.044	(0.13)**	1.780	(0.17)**	0.020	(0.19)
$br_{jt} * D^3_{MS} * D^2_{NT}$	-0.436	(0.14)**	-0.181	(0.16)	1.927	(0.22)**	2.502	(0.24)**	3.509	(0.33)**	1.428	(0.32)**
$br_{jt} * D^3_{MS} * D^3_{NT}$	1.301	(0.39)**	2.069	(0.45)**	5.545	(0.81)**	6.933	(0.90)**	7.844	(1.29)**	5.694	(1.09)**
Constant	0.413	(0.04)**	0.365	(0.04)**	-0.339	(0.05)**	-0.392	(0.06)**	-0.465	(0.05)**	0.112	(0.10)
Stock fixed effects?	no		yes		no		yes		yes		yes	
adj. R^2	0.007		0.011		0.024		0.031		0.039		0.027	
Observations	63498		63498		41855		41855		31167		20764	

Heteroscedasticity–robust standard errors shown in parenthesis. These standard errors allow for free correlation of the residuals within same–stock observations. Statistical significance on the 1/5/10% level are indicated by **/*/+

Table 5: Herding and Returns: Robustness

This table reports the results of a regression of the excess return of stock j on day t (r_{jt}, in percent, computed over the DAX100) on the buyers ratio br_{jt}, with the buyers ratio fully interacted with dummy variables indicating market-value share terciles ($D^1_{MS} - D^3_{MS}$) and dummies indicating the number–of–traders groups (D^1_{NT} for observations with only one trader, D^2_{NT} with two to four traders, and D^3_{NT} five or more traders). The market value share MS_{jt} was computed as the number of stocks held by all brokerage customers divided by the total outstanding stock, from Datastream.
In the first column, labelled "including all dummies", we include all of the above dummies in addition to the interaction with the buyers ratio. (coefficients not shown)
In the second column, labelled "with day fixed effects", we replace the company fixed effect with day fixed effects. (coefficients not shown)
In the third column, labelled "with lagged returns", we add the excess return of stock j on the previous trading day. (r_{jt-1})
In the fourth column, labelled "smaller top-NT-group", we redefine the number–of–trader groups to be D^1_{NT} for observations with only one trader, D^2_{NT} with two to eight traders, and D^3_{NT} nine or more traders.

All regressions are based on transactions that were market orders.

	Dependent Variable: r_{jt}							
Variation:	including all dummies		with day fixed effects		with lagged returns		smaller top-NT-group	
	coeff	se	coeff	se	coeff	se	coeff	se
r_{jt-1}					0.026	(0.01)**		
$br_{jt} * D^1_{MS} * D^1_{NT}$	0.290	(0.12)*	0.540	(0.10)**	0.190	(0.11)+	0.190	(0.11)+
$br_{jt} * D^1_{MS} * D^2_{NT}$	-0.462	(0.22)+	0.506	(0.16)**	0.320	(0.20)+	0.407	(0.24)+
$br_{jt} * D^1_{MS} * D^3_{NT}$	-1.162	(0.52)+	0.897	(0.36)*	1.051	(0.54)+	0.861	(0.51)+
$br_{jt} * D^2_{MS} * D^1_{NT}$	0.795	(0.13)**	0.641	(0.11)**	0.608	(0.12)**	0.583	(0.12)**
$br_{jt} * D^2_{MS} * D^2_{NT}$	1.805	(0.28)**	1.647	(0.19)**	1.807	(0.21)**	2.158	(0.24)**
$br_{jt} * D^2_{MS} * D^3_{NT}$	2.503	(1.25)+	3.425	(0.68)**	4.301	(0.67)**	5.373	(1.29)**
$br_{jt} * D^3_{MS} * D^1_{NT}$	1.167	(0.13)**	0.927	(0.13)**	1.043	(0.13)**	1.040	(0.13)**
$br_{jt} * D^3_{MS} * D^2_{NT}$	2.701	(0.31)**	1.806	(0.21)**	2.430	(0.24)**	3.010	(0.27)**
$br_{jt} * D^3_{MS} * D^3_{NT}$	7.794	(1.72)**	5.351	(0.78)**	6.550	(0.86)**	9.221	(1.66)**
Constant	-0.131	(0.13)	-0.309	(0.05)**	-0.390	(0.06)**	-0.368	(0.06)**
Stock fixed effects?	yes		no		yes		yes	
adj. R^2	0.033		0.069		0.031		0.030	
Observations	41855		41855		41322		41855	

Heteroscedasticity–robust standard errors shown in parenthesis. These standard errors allow for free correlation of the residuals within same–stock observations. Statistical significance on the 1/5/10% level are indicated by **/*/+

Table 6: Herding and Future Returns

Results of a regression of the excess returns one, two, and three (trading) days into to the future, on the buyers ratio interacted with the nine dummies indicating three market–value–share terciles and three number–of–trader groups. See Table 4 for a more detailed description.

	Dependent Variable:					
	r_{jt+1}		r_{jt+2}		r_{jt+3}	
	coeff	se	coeff	se	coeff	se
$br_{jt} * D^1_{MS} * D^1_{NT}$	0.494	(0.11)**	0.026	(0.09)	0.129	(0.09)
$br_{jt} * D^1_{MS} * D^2_{NT}$	0.454	(0.13)**	0.100	(0.12)	-0.104	(0.12)
$br_{jt} * D^1_{MS} * D^3_{NT}$	0.574	(0.20)**	0.303	(0.16)+	-0.244	(0.15)
$br_{jt} * D^2_{MS} * D^1_{NT}$	0.410	(0.09)**	0.170	(0.10)+	-0.400	(0.09)**
$br_{jt} * D^2_{MS} * D^2_{NT}$	0.570	(0.15)**	0.013	(0.18)	-0.187	(0.14)
$br_{jt} * D^2_{MS} * D^3_{NT}$	1.362	(0.36)**	-0.627	(0.31)*	-0.723	(0.27)**
$br_{jt} * D^3_{MS} * D^1_{NT}$	0.429	(0.11)**	-0.165	(0.11)	-0.171	(0.11)
$br_{jt} * D^3_{MS} * D^2_{NT}$	1.110	(0.18)**	-0.274	(0.16)+	-0.669	(0.17)**
$br_{jt} * D^3_{MS} * D^3_{NT}$	1.186	(0.32)**	-0.219	(0.28)	-0.562	(0.30)+
Constant	-0.165	(0.03)**	0.099	(0.03)**	0.215	(0.03)**
Stock fixed effects?	yes		yes		yes	
adj. R^2	0.004		-0.000		0.001	
Observations	41246		40960		40830	

Heteroscedasticity–robust standard errors shown in parenthesis. These standard errors allow for free correlation of the residuals within same–stock observations. Statistical significance on the 1/5/10% level are indicated by **/*/+