Geographic Investment Focus and its Impact on Herd Behavior – Evidence from the German Equity Fund Market

ALEXANDER FRANCK[*] and ANDREAS WALTER[†]

[*] Justus-Liebig University Giessen, Department of Financial Services, Licher Strasse 74, D-35394 Giessen, Germany; Email: Alexander.Franck@wirtschaft.uni-giessen.de

[†] Justus-Liebig University Giessen, Department of Financial Services, Licher Strasse 74, D-35394 Giessen, Germany; Email: Andreas.Walter@wirtschaft.uni-giessen.de

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Abstract

We examine the herd behavior among equity funds in Germany based on a large and unique sample of funds from 2000 to 2009. We show that a large portion of the detected herding can be explained by identical trading among funds of the same investment company. However, we also find statistically significant stock herding among funds belonging to different fund families. As existing herding studies usually analyze herd behavior within a purely national stock environment, we contribute to the literature by investigating mutual fund herding in international stocks. Funds with different geographic investment focuses clearly differ in the number of potential stocks in the investment universe. We find the most pronounced levels of herding for funds choosing their portfolio stocks from a broad, international investment universe. To analyze the herd behavior of individual funds, we introduce a new and intuitive way to assign levels of herding to funds according to their trading activity within a given period. By dividing the fund sample into subgroups of individual herding levels, we can analyze the impact of herding strategies on fund performance. It seems that the best-performing funds, on the one hand, buy stocks with the herd and, on the other hand, do not sell their stocks when others do.

Keywords**:** *Herding behavior, behavioral finance, asset allocation, mutual funds*

JEL classification: *D82, G11, G23*

1 Introduction

By the end of 2009, 6.6 million Germans were invested in equity funds. Compared to 1997, the number of equity fund shareholders had increased by 4.3 million (+185.6%). In contrast, only 3.6 million investors had direct holdings in individual stocks.[1] According to the German Federal Association of Investment Companies (Bundesverband Investment und Asset Management e.V., BVI), total assets under management of equity funds licensed for distribution in Germany reached €197.7 billion at the end of 2009.[2] These numbers underline the importance of professional asset managers for the stock market and the contributors of capital. Apparently, equity funds are among the most popular investment vehicles for private and corporate investors.[3]

The notion that fund managers are highly educated and experienced players within the capital markets is opposed by empirical studies showing that managers largely fail to beat their respective benchmarks (e.g. Malkiel, 1995). Besides the typical performance evaluation in relation to an index, fund managers are systematically evaluated and measured in relation to peer groups (Lakonishok et al., 1992). Out of reputational concerns, managers might copy trading decisions of colleagues to avoid falling behind the peer group (Scharfstein and Stein, 1990). As herding seems to be a solid way to maintain a competitive performance, it is also associated with less working effort for fund managers (Lütje, 2009). Despite extensive research provided by buy-side as well as sell-side analysts, limited time capacities might lead professional managers to imitate trades of their peers, at least to a certain extent.

According to Bikhchandani and Sharma (2001), we can categorize the theoretical herding literature into two general groups. The first group includes theories that explain herd behavior as a result of unintentionally related trades and is thus called unintentional or spurious herding. The second group describes herd behavior as intentional reproduction of others' trading decisions.

Unintentional herding is usually fundamentals-driven: since all investors possess the same information, trading decisions are often identical and cause high levels of herding for specific stocks (e.g. Froot et al., 1992 or Hirshleifer et al., 1994). Assuming that asset managers have similar educational backgrounds, they might also analyze information analogously. We therefore classify unintentional herding through correlated private signals as

[1] Data provided by DAI (Deutsches Aktieninsitut e.V.).

[2] According to Deutsche Börse the market capitalization of all German equities was €900.7 billion at the end of 2009.

[3] See BVI-Investmentstatistik (2011).

investigative herding (Sias, 2004). Moreover, Falkenstein (1996) supposes that managers avoid certain stocks, such as stocks with low liquidity or little analyst coverage. Derived from Bennett et al. (2003) we summarize the theories based on such assumptions as *characteristic herding*. The decision of buying past winners and selling past losers might be driven by the employ of momentum investment strategies (De Long et al., 1990). If enough funds follow this investment strategy, we would also expect to see them herd into and out of the same stocks in a timely manner. A further potential explanation of unintentional herding is that fund managers might also follow *fads* (Friedman, 1984), causing significant stock herding within certain industries as funds herd into or out of a particular group of stocks.

Intentional herding originates from two basic theories. Either managers herd due to reputational reasons or due to a lack of information. *Reputational herding* originates from Keynes' assumption (1936, p. 158) that "it is better for reputation to fail conventionally than to succeed unconventionally." Scharfstein and Stein (1990) ascribe this agency interpretation to mutual fund herding by arguing that managers might disregard private information and rather follow the crowd out of reputational concerns. Additionally, Hirshleifer and Teoh (2003) conclude that reputation-based models can best explain robust and stable herd behavior in capital markets. In contrast, the alternative intentional herding explanation claims the cause of herding to be imprecise private information. Imitating prior trades of better informed fund managers seems to be particularly rewarding when information is sparse (Bikhchandani et al., 1992). As a result, *informational cascades* might evolve as several fund managers intentionally trade alike. Imitation thus causes high levels of herding within specific stocks.

In order to detect herding empirically, most studies employ a herding measure developed by Lakonishok, Shleifer, and Vishny (1992; hereafter the LSV measure). With respect to herding by money managers, Lakonishok et al. (1992) find only weak evidence for herding among US pension funds over the period from 1985 to 1989. For the US mutual fund industry, Grinblatt et al. (1995) and Wermers (1999) identify positive-feedback trading strategies that account for most of the detected levels of herding. The average LSV measure for US equity funds found by Wermers (1999) is only slightly higher than the one detected by Lakonishok et al. (1992) among pension funds. Employing a different measurement approach, Sias (2004) detects strong evidence of herding among institutional investors. He defines herding as a positive correlation of institutional investors' demand for a stock in a given period with their demand in the preceding quarter. Further, his correlation analysis reveals that US institutional investors' herd behavior is more strongly related to prior institutional demand than prior stock returns. In other words, herding results from managers inferring information from each other's trades. For the UK mutual fund market, Wylie (2005) finds a modest level of the LSV measure across small and large equities, however little herding in other stocks or industries.[4] Interestingly, fund managers in the UK seem to be contrarian traders, i.e. herding out of stocks that recently performed well.

A first assessment of herding among German fund managers is provided by Oehler (1998). Although he finds market-wide herding among 28 German equity funds, his results are not comparable to the studies mentioned above due to the use of a different measurement approach. Walter and Weber (2006) compare their herding results within the German equity market to the results of other studies employing the LSV measure. They show that a large part of the detected herding is accounted by changes within the DAX 30 or DAX 100 index compositions. In a recent contribution, Kremer and Nautz (2011) confirm institutional herding across stocks listed in the three major German stock indices (i.e. DAX 30, MDAX, SDAX), in particular herding across large stocks.

Our study contributes to the herding literature regarding three aspects. Firstly, we provide the most comprehensive study on the German mutual fund industry by analyzing international stock holdings of a large sample of 1,181 equity funds that were licensed for distribution in Germany during the 10-year period from January 2000 to December 2009. Through the use of FactSet's LionShares database, we do not have to hand-collect the portfolio data, as done in most fund herding studies for Germany, and can thus broaden our analysis to a much bigger fund sample and stock universe.

Secondly, we extend the analyses on herd behavior by investigating mutual fund herding in different stock universes. Existing studies usually examine herding within an exclusively national stock environment.[5] Funds with a pure German equity investment objective only constitute 6.5% of the number of funds within our whole sample. Due to its unrestricted, international stock universe, our sample allows us to set up subgroups of equity funds according to their geographic investment focus categorized by the BVI[6] and analyze their herding behavior separately.

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[4] Herding studies for other European capital markets include e.g. Lobão and Serra (2006) for Portugal or Voronkova and Bohl (2005) for Poland.

[5] See for example Grinblatt et al. (1995), Wermers (1999), Walter and Weber (2006), or Kremer and Nautz (2011). In a recent working paper, Oehler and Wendt (2009) also include international stocks to their data. However, their sample of 79 funds is rather small.

[6] Of the 1,181 equity funds in our sample, the BVI classifies 901 as funds with a specific geographic investment focus.

Thirdly, we introduce a simple and intuitive way to assign levels of herding to individual funds in order to differentiate between managers that herd and those that do not. Thereby, we can analyze whether funds exhibit different levels of buy-herding and sell-herding, if they show similar herding intensities within a given and a succeeding period, and if herding intensities have an impact on fund performance.

Across the entire sample of equity funds, we find a LSV measure of 4.28% for the 10-year observation period. This average can be interpreted as meaning that if 100 funds trade a given stock in a given period, then approximately four more funds trade in the same direction than would be expected if each of them chose its stocks randomly and independently. To a significant extent, the detected herding can be explained by funds within the same mutual fund management company trading alike. However, we also find significant levels of herding among funds belonging to different fund families.

Dividing our sample into subgroups of funds, we detect higher levels of herding among managers that choose their portfolio holdings from a broad, international stock universe. Furthermore, we find the most extensive herd behavior among the largest funds in terms of both equity assets under management and number of stocks held.

Our analysis on herd behavior of individual funds reveals that significant buy-herding funds do not seem to herd with the same intensity when selling stocks and vice versa. Within the two groups of funds that herd least and that herd most, we discover 33% of the funds to show similar levels of herding again in the next period. Furthermore, we find the strongest buy-herding funds to perform significantly better than funds that herd less. On the sell-side however, we find the best-performing funds within the group of the least herding funds.

The remainder of the paper is arranged in three sections. The following section discusses our database, presents some descriptive statistics, and describes the methodology employed to detect herd behavior. Section 3 introduces and interprets our empirical results of herding across all funds, fund families, different subgroups of funds, and individual funds. Finally, section 4 concludes.

2 Data sample and methodology for measuring herding

2.1 Description of database

Our empirical study focuses on equity funds distributed in Germany, regardless of their general investment strategies. We construct our fund universe by filtering the FactSet Research Systems' lists of active and liquidated mutual funds for those that were licensed for distribution in Germany for at least one year during our investigated period from 01 January, 2000 to 31 December, 2009. Therefore, our sample is not prone to the well documented survivorship bias.[7] The FactSet mutual fund holdings database LionShares provides us with the global equity ownership data of the mutual fund portfolios. Our database consists of the funds' equity holdings on a semi-annual basis and general information on the fund managers of 1,181 equity funds. We only include funds that are classified as equity funds by the BVI in our sample and attain further information regarding the funds' investment focus from the quarterly BVI statistics. Finally, we receive the information on the funds' returns and historic prices of the stocks contained in the funds' portfolios from Datastream.

Legal regulations stated in the German InvG (Investmentgesetz) require investment companies to report their funds' trading activities semi-annually to the BAFIN (German Financial Supervisory Board) and to the Deutsche Bundesbank (Federal Bank of Germany).[8] Of the 1,181 observed funds, 697 publish their reports in the second and in the fourth quarter of the year, the remaining 484 in the first and third quarter. We follow the suggestion of Walter and Weber (2006) and only include mutual funds that either report in a June to December cycle or in a March to September cycle in our sample. A different approach is to synchronize data by extrapolating the reported holdings on dates not matching the given reporting cycles to the nearest dates of the given reporting cycles (Wermers, 1999). Since this process might dilute data quality, we do not apply it to reports that are not in line with the main reporting cycles. Walter and Weber (2006) further stress the point that herding analyses are only meaningful if fund managers are not restricted and can adjust the portfolios in accordance with their expectations of market development. Therefore, the sample is free of passively managed index funds.

We identify trading activity of each equity fund based on changes in its semi-annual stock portfolio. A stock being bought or sold in a given period by at least one fund is defined as a stock-period. In order to avoid dilution of data quality, we ignore a fund in this and the next stock-period when calculating the degree of herding, if holding information in a specific period is missing. In addition, stock-periods in which no trading occurs but equity stakes change due to capital actions, for example stock splits, are also excluded. We receive the necessary data on capital actions from Datastream.

[7] According to Wylie (2005), the analyses of survivorship biased databases misstate the real level of herding, since the reason for the observed funds' survival might be conditional upon the avoidance of trading strategies that lead to liquidation or merger with other funds.

[8] The regulations are stated in §44 InvG.

2.2 Descriptive statistics

Table 1 shows a descriptive summary of our database. The number of funds included in our sample increases steadily from 2001 to 2007 and again rises from 2008 to 2009 (not displayed in Table 1). The years presented in Panel A show an increase from 555 active funds in 2001 to 715 funds in 2009.[9] Across all ten years, the average number of funds observed per year is 654. In contrast to previously published studies on herding behavior in the German investment fund market, we do not limit our analysis to the major fund providers, nor do we exclude funds that do not primarily invest in German stocks. With a 10-year window, we also derive our findings from a much larger observation period.

Insert Table 1 about here.

Panel B summarizes the net equity assets of our fund universe.[10] The mean equity value per fund varies significantly over time and so does the total equity value of all funds. Across all ten years, the average equity value per fund is €274.1 million. Regarding the total market value of all funds, the data reveals the recovery of the fund market in 2005 and its plunge in the years of the financial crisis following 2007. Within the investigation period, our sample shows its all-time high total equity value of €213.1 billion in 2007 and its all-time low of €85.9 billion in 2002 (not displayed).[11] From Panel C we can see that the average number of stocks held per fund rises steadily over the investigation period from 52 stocks in 2001 to 79 in 2009. While the annual portfolio growth rate is quite low in the years up to 2007, we observe a significant average increase of eleven stocks per fund in the year of 2009 (68 stocks were held per average fund at the end of 2008).

Panel D displays a short summary of the inferred trades initiated by the fund managers of our sample. We document a steady yearly increase of the number of trades and 32,146 trades within an average six-month trading period. Until 2006, the funds exhibit a higher proportion of trades on the buy-side. Finally, we display the trading frequency of an average fund manager as proportion of stocks traded to stocks held. The trading rate increases steadily over the 10-year period, with a mean of 83.3%.

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[9] To provide a comprehensive descriptive summary, the two different reporting cycles are here regarded as one and data from March and September is postponed to June and December.

[10] We calculate the equity values by multiplying the portfolio stakes received from FactSet with the respective historic stock prices extracted from Datastream.

[11] Although we only have information regarding the funds' equity holdings, our dataset covers between 62% (in 2001) and 93% (in 2009) of the total assets under management of all equity funds covered by the BVI.

2.3 Methodology

2.3.1 The LSV measure of herding

In accordance with most other studies on mutual fund herding, we follow the measurement approach introduced by Lakonishok et al. (1992).[12] This allows us to compare our results with prior herding studies on the German and international stock markets.

The LSV measure defines herding as the average tendency of a given subgroup of managers to accumulate on the same side of the market in a given stock within the same time period, more often than would be expected if the managers traded independently. The herding measure $HM_{i,t}$ for stock i in period t (stock-period i,t) is expressed as follows:

$$HM_{i,t} = | p_{i,t} - p_t | - AF_{i,t} \qquad \text{with} \qquad p_{i,t} = \frac{B_{i,t}}{B_{i,t} + S_{i,t}}, \tag{1}$$

where $B_{i,t}$ ($S_{i,t}$) "counts" the number of funds buying (selling) a stock i in period t. More precisely, $p_{i,t}$ is the proportion of all funds trading stock-period i,t that are purchasers. The buy probability p_t represents the overall signal in the market and is calculated as the number of buyers in t aggregated across all stocks i divided by all trades n (i.e., buys and sells) in t:

$$p_t = \frac{\sum_{i=1}^{I} B_{i,t}}{\sum_{i=1}^{I} n_{i,t}} \quad . \tag{2}$$

This buy probability serves as expected proportion of buyers that stays constant across all stocks in a given period t, changing only over time. The subtraction of p_t corrects for "market-wide herding" that might be the result of large net inflows.

If no herding exists, the herding measure should be zero. However, the expression ($|p_{i,t} - p_t|$) is defined in absolute terms and without subtracting an adjustment factor $AF_{i,t}$ likely to be greater than zero. $AF_{i,t}$ is the expected value of $|p_{i,t} - p_t|$ which we calculate under the assumption that trades follow a binomial distribution with two possible outcomes: $B_{i,t}$ (success) and $S_{i,t}$ (failure). In other words, the adjustment factor simply controls for the probability that the observed trading behavior is the result of a random process. Under the null hypothesis of no herding, the probability of $B_{i,t}$ is p_t.

[12] See Oehler (1998), Wermers (1999), Sias (2004), or Frey et al. (2007) for modified measures of herding and portfolio changes.

A positive $HM_{i,t}$ value that significantly differs from zero indicates a tendency of a group of funds to trade a given stock together and in the same direction in a given period above random distribution of trade decisions. To measure the extent to which a specific subgroup of funds herds in a typical stock-period during an observed time frame, we need to average the LSV herding measures, calculated for the group, across all stock-periods (we denote the average as HM). Again, a positive and statistically significant HM is an indication of herding by the observed subgroup of funds. In accordance with Wermers (1999), we compute the adjustment factor $AF_{i,t}$ and the expected proportion of buyers p_t based only on trading by a given subgroup.

Although the LSV measure can be regarded as the standard measure for empirical herding studies, there also exist some drawbacks.[13] One elementary downside is that it does not allow differentiating between fund herding on the buy-side and sell-side. We thus adopt the modification from Wermers (1999) and calculate "conditional" herding measures based on the direction of the trades:

$$\begin{aligned} BHM_{i,t} &= HM_{i,t} \mid p_{i,t} > p_t \\ SHM_{i,t} &= HM_{i,t} \mid p_{i,t} < p_t \end{aligned} \tag{3}$$

Letting $BHM_{i,t}$ equal the "buy-herding measure" and $SHM_{i,t}$ the "sell-herding measure", we average the two directional measures separately from each other. In a comparison, we can then analyze whether certain subgroups of funds herd more frequently on the sell-side or the buy-side of the stocks traded.

2.3.2 Applying the LSV measure to individual mutual funds

Another drawback of the LSV measure and its refinement by Wermers (1999) is the fact that we cannot actually distinguish the specific managers that herd from those that do not (Bikhchandani and Sharma, 2001). We thus expand the measures presented above by applying them to individual funds in a simple and intuitive way.

We assign all calculated measures N of directionless and directional stock herding to individual funds F according to their trading activity within a given period t:

[13] See Wylie (2005) and Walter and Weber (2006) for an overview and discussion on the shortcomings of the LSV measure.

$$
\begin{aligned}
HM_{F,t} &= \sum_{i=1}^{N} HM_{i,t} \times \frac{tv_{F,i,t}}{tv_{F,t}} && | \; B_{F,i,t} > 0 \; \vee \; S_{F,i,t} > 0 \\
BHM_{F,t} &= \sum_{i=1}^{N} BHM_{i,t} \times \frac{pv_{F,i,t}}{tv_{F,t}} && | \; p_{i,t} > p_t \; \wedge \; B_{F,i,t} > 0 \\
SHM_{F,t} &= \sum_{i=1}^{N} SHM_{i,t} \times \frac{sv_{F,i,t}}{tv_{F,t}} && | \; p_{i,t} < p_t \; \wedge \; S_{F,i,t} > 0
\end{aligned}
\tag{4}
$$

with $tv_{F,t}$ being the total trading value of fund F in period t. Further, $tv_{F,i,t}$ stands for a fund's trading value, $pv_{F,i,t}$ for its purchase value, and $sv_{F,i,t}$ for its sale value of stock i in t.

Within every formation period, the calculated measure of directionless herding ($HM_{i,t}$) and, depending on whether the stock was more often bought than expected or less often, either the measure of buy-herding ($BHM_{i,t}$) or sell-herding ($SHM_{i,t}$) for each stock is assigned to all funds trading the stock. For example, a fund that buys a stock within a given period is assigned the stock's $HM_{i,t}$ and, if the stock was more often bought than expected, the stock's $BHM_{i,t}$ of the respective period. Thereby, each stock herding measure is weighted by the proportion of its trading value to the fund's total trading value within the given period.[14] In every period, we then calculate the individual herding intensities for each fund (i.e. $HM_{F,t}$, $BHM_{F,t}$, and $SHM_{F,t}$) by cumulating its weighted stock herding measures.[15]

3 Results

3.1 Overall herding results and results of other studies

Panel A of Table 2 presents results of the LSV measure of herding (*HM*) applied to the entire fund universe. Requiring at least two funds to trade stock i in period t, the *HM* value calculated across all stock-periods equals 4.28%. We impose this minimum trading activity restriction in accordance with previous literature.[16] An average herding measure of 4.28% means that if 100 funds trade a given stock-period, then approximately four more funds trade in the same direction than would be expected if each of them chose its stocks randomly and independently. In his herding study, Wermers (1999) imposes a hurdle of five funds trading a specific stock-period, arguing that only a few funds trading in the same direction would not

[14] To avoid overstating individual stock herding measures within internal fund herding levels, we weight a stock's herding measure by the trade's share of the fund's total trading value within the respective period.

[15] Grinblatt et al. (1995) also develop a fund herding measure for individual funds. However, their measure only averages the individual level of directionless herding across all periods, making it not possible to compare individual fund herding by direction or across time.

[16] See for example Scharfstein and Stein (1990), Bikhchandani et al. (1992), Wylie (2005), and Walter and Weber (2006).

qualify as a herd. Table 2 also reports results for the restriction of at least five funds being active in a given stock-period. Both, the two and five funds trading restrictions, lead to similar results. Requiring at least five funds to trade stock *i* in period *t*, the average level of herding calculated across all stock-periods equals 3.89% (see Panel A), which is only slightly lower than the one calculated for the two funds trading hurdle. In consequence, we will conduct further analyses only on stock-periods traded by at least two funds.[17]

Insert Table 2 about here.

Results from other studies are presented in Panel B. In comparison to our sample, most other studies are based on a smaller stock or fund universe across a shorter time frame. Only Wermers (1999) covers more stock-periods within his 20-year herding sample. The average LSV measure of 3.89% if at least five funds trade a given stock in our sample is similar to the results for American mutual funds found by Grinblatt et al. (1995), i.e. 4.32%, and Wermers (1999), i.e. 3.40%. However, Wermers (1999) finds a slightly higher level of herding of 5.10% using a semi-annual period as unit of time measurement. Also based on semi-annual reports, Wylie (2005) documents a rather low herding measure of 2.60% within a minimal two funds trading restriction and 2.50% within a minimal five funds trading restriction for UK mutual funds.

The results for Germany need to be differentiated between private and institutional investors. On the one hand, Dorn et al. (2008) find significant levels of herding of 8.30% for retail investors of a large German discount broker. On the other hand, Walter and Weber (2006) and Kremer and Nautz (2011) investigate the herd behavior among German institutions. While Kremer and Nautz (2011) only find a LSV measure of 2.29%, Walter and Weber (2006) detect higher levels of herding around 5%. Although our results lie somewhere in the middle, we restrain from a direct comparison since we do not limit our analyses to German stocks and compute results valid beyond the German stock market.

If we assume that less developed financial markets show lower information efficiency, we would expect fund managers within these markets to be particularly prone to any information available. Analyzing the trades of one's peers might become an important source of information, leading to herd behavior as informational cascades develop (Bikhchandani et al., 1992). In accordance with these theoretical predictions, empirical findings exhibit herding

[17] Results based on the five funds trading hurdle are available upon request.

measures of 12.44% among Portuguese mutual fund managers (Lobão and Serra, 2006) and 22.60% among Polish pension fund managers (Voronkova and Bohl, 2005).

3.2 Herding within mutual fund management companies

Pronounced levels of stock herding computed for the entire fund universe might be the result of identical trading among funds of the same fund family (Wermers, 1999). Herd behavior could be triggered by managers reacting to the same "private" signals derived from internal stock recommendations (Frey and Herbst, 2011) or colleagues trading together for lower unit trading costs (Wermers, 1999). Furthermore, it is likely that, within a company, higher transparency eases the imitation of trades of colleagues (Bikhchandani et al., 1992). Reputation-based herding models (e.g. Scharfstein and Stein, 1990) can explain high levels of herding if colleagues are evaluated against each other. Finally, managers of the same investment company simply have more possibilities of informally communicating with each other. The exchange of ideas and opinions regarding certain stocks among colleagues can explain higher levels of herding within a given mutual fund family.

To investigate the issue of herding among funds of the same investment company, we compute the levels of herding within each of the five biggest mutual fund companies separately. We rank the companies by the number of funds they distributed in our 10-year sample.[18] Panel A of Table 3 shows that the average LSV measures vary significantly by company. Moreover, all means are above 4% and the *HM* averaged across all computed $HM_{i,t}$ equals 6.56%. With all means being statistically significant, we can confirm the theoretical predictions of stock herding within single fund families. Nevertheless, we still find a high and significant average level of herding calculated across all five companies (*HM* of 5.13%). In accordance with our prior results, herding seems to be apparent beyond single corporate walls.

Insert Table 3 about here.

Panel C shows average LSV measures using the mutual fund company as measurement unit, not single funds. Corresponding to Wermers (1999), we sum the holdings over all funds within one company at each reporting date. An investment company is considered a buyer (seller) of a given stock if the cumulated holdings increase (decrease) within a given stock-period. We average the LSV measures across different subperiods and

[18] Since it is not our goal to document which mutual fund company herds more or less, we do not display the names of the individual firms.

constantly find a decreased level of herding of about 2%. This level is similar to Wermers' (1999) results and is consistent with our findings in Panel A, indicating on the one hand that funds within the same investment company trade alike. On the other hand, herding levels of roughly 2% within all subperiods still confirm significant herding across different fund companies. On average, the number of different fund families on the same side of the market exceeds expectations by about 2%, whereas for single funds, the findings exceed expectations by 4% (see Table 2). In the following of the paper, we will continue using single funds as measurement unit in order to analyze herd behavior within different fund subgroups.

3.3 Herding segregated by fund characteristics

3.3.1 Herding segregated by funds' geographic investment focus

As a statistical approach, the LSV measure is unable to differentiate between intentional and unintentional herding and cannot identify the underlying reasons for a trade. Investigating subgroups of funds might help explain theoretical models regarding managers' intention to herd. Moreover, we would expect higher levels of herding among funds with similar investment objectives than among the entire fund universe (Walter and Weber, 2006). Wermers (1999) argues that in a heterogeneous universe of funds, a purchase by one fund is more likely to coincide with a sale by another fund.[19]

Because our database is not restricted to equity funds primarily investing in German stocks, we can divide our sample according to different geographic investment focuses. This separation is of particular interest, since other herding studies on mutual funds have merely analyzed funds' herd behavior beyond national stocks.[20] The geographic investment focuses classified by the BVI and mostly present in our fund sample are German stocks, European stocks, and global stocks containing 77, 248, and 231 funds. As these geographic clusters clearly differ in the number of potential stocks in the investment universe, fund managers can devote more or less time to single securities. For example, funds with a German investment focus have fewer stocks to choose from than funds that invest in European stocks. Therefore, more research capacity can be allocated to single stocks and managers should be less prone to

[19] Nevertheless, Wermers (1999) finds levels of herding computed for the entire fund universe not significantly lower and in several cases higher than the levels computed for specific subgroups.

[20] See for example Grinblatt et al. (1995), Wermers (1999), Walter and Weber (2006), or Kremer and Nautz (2011). Oehler and Wendt (2009) also investigate subgroups of funds with geographic investment focus. However, their sample of 79 funds only consists of 43 geographic-orientated funds from 2000 to 2005 and is thus a lot smaller than our sample.

follow trades of others but rather trust on their accurate private information. The search problem when buying a stock increases with the number of stock alternatives.[21]

Jacob et al. (1999) argue that, on the one hand, larger numbers of companies followed by a single research analyst can result in reduced focus and therefore lower accuracy. On the other hand, following larger numbers of companies could be associated with higher forecast accuracy, as more capable analysts are likely to be assigned greater responsibilities. Furthermore, following several companies might provide analysts with deeper insights into industry trends. In their empirical analyses they find that the more companies an analyst follows, the less accurate her forecasts are. They ascribe this result to a diffusion-of-focus effect. In a similar study, Clement (1999) documents that analysts' forecast accuracy is negatively associated with portfolio complexity, which he measures as number of companies and industries followed by the analyst. Accordingly, professional fund managers choosing their stocks from a broad stock universe are confronted with an increased portfolio complexity and a diffusion-of-focus effect. In combination with limited timely capacity and associated high search costs, these factors might lead managers to imitate trades of other funds causing high levels of herding.

Table 4 presents directionless and directional herding measures for the three subgroups of funds. Panel A presents *HM* averaged across all funds with a German equity focus. We find a herding measure significantly lower (*HM* of 2.55%) than the one among the entire fund universe (4.28%). In the rather small German stock market, fund managers seem to be more capable to gather and manage information independently. Attention-driven trades (Barber and Odean, 2008) might not be as rewarding and the level of herding on the buy-side and sell-side is rather moderate. Apart from the theoretical considerations, we would expect funds licensed for distribution in Germany to have expertise in the German capital market. As a result, managers might rather trust their own information on German stocks than follow other trades and thereby create a herd (informational cascade, e.g. Bikhchandani et al., 1992).

Insert Table 4 about here.

Panel B shows the herd behavior of funds with a European equity focus and compares it to the *HM* of funds focusing on German stocks. Managers of European equity funds have to choose their portfolio holdings from a broader stock universe than managers restricted to

[21] Barber and Odean (2008) document that in an environment with many stock alternatives, individual investors are more likely to buy stocks that have recently caught their attention.

German stocks. The *HM* of 4.12% is remarkably higher than the *HM* calculated across the German equity focused funds. Thus, these managers seem to trade the same stocks to a greater extent even though they have a lot more options. In accordance with our predictions, the broader stock universe leads managers to imitate trades of others due to a lack of private information (Bikhchandani et al., 1992), a diffusion-of-focus effect (Jacob et al., 1999), or due to attention-driven trading decisions (Barber and Odean, 2008). Higher buy-herding levels than sell-herding levels (4.57% vs. 3.63%) could be an indicator for attention-driven purchase decisions. Going along with these observations, Panel C reveals that funds with a global equity focus exhibit the highest levels of herding amongst the subgroups (*HM* of 4.97%). It seems as if the degree of herding is positively correlated to the size of the stock universe from which managers can choose their portfolios.

3.3.2 Herding segregated by fund size

If the size of the stock universe has an effect on the level of herding among funds, we need to further investigate whether the size of the funds themselves has a similar effect as well. Due to an assumed high research disposal and capacity, theoretical assumptions suggest that larger funds should be more reluctant to follow informational cascades (Bikhchandani et al., 1992). As they receive more detailed information, they should be able to trust more on their private signals. Accordingly, in their empirical analysis, Frey and Herbst (2011) find that fund managers trade most strongly in reaction to recommendation changes by buy-side analysts. As stock prices do not reflect the information instantly, it seems to be profitable to respond to private signals inferred from internal recommendations of buy-side analysts working for the same investment company. Again, large funds belonging to global investment companies may rely on a broad range of buy-side analysts and should thus be able to trade independently.

At the beginning of each formation period, we allocate every fund to a size quintile (Q1 to Q5) based on the fund's net equity assets (with Q1 including the smallest funds). We then compute *HM* across all years separately for each quintile to evaluate whether the degree of herding depends on the size of a fund.

Panel A of Table 5 shows the average herding measures segregated by size in each formation period. In contrast to the theoretical considerations, our results reveal that large funds seem to herd more than small and in particular more than medium-sized funds. The difference in means between the *HM* of the smallest funds (4.14%) stated in Q1 and the largest funds (5.68%) stated in Q5 amounts to 1.55% and is statistically significant at the 1% level. These results also oppose the observations of Walter and Weber (2006), who do not find an impact of fund size on herding in their fund sample.[22] Exceptionally high levels of herding within the group of large funds might be explained as follows: firstly, large funds are usually managed by senior fund managers with a rather high level of reputation in the industry. Thus, these managers might have an incentive to secure their reputation by moving with the crowd (Scharfstein and Stein, 1990). Secondly, information inferred by trading of highly reputable managers is likely to be of high precision. Thus, informational cascades might develop rapidly in the group of senior fund managers (Bikhchandani et al., 1992). In addition, herding detected amongst the biggest funds (Q5) might be triggered by funds belonging to the same mutual fund family and thus reacting to the same "private" signals derived from internal stock recommendations.

With respect to the smallest funds, we find higher levels of herding in Q1 compared to the three remaining groups, Q2 to Q4. If we assume that the smallest funds are usually managed by younger, inexperienced fund managers, reputation-based herding models (e.g. Scharfstein and Stein, 1990) could also explain high levels of herding within our smallest fund subgroup (Q1). Career concerns might give young professionals an incentive to herd (Keynes, 1936). As a matter of fact, Chevalier and Ellison (1999) find more conventional portfolios with less unsystematic risk among younger fund managers. Hong et al. (2000) document that younger analysts are punished more severely for poor forecasts and forecast boldness. Consequently, they detect more herding among younger analysts than among their experienced counterparts.

Insert Table 5 about here.

Another way to segregate funds by size is to allocate every fund to a size quintile (Q1 to Q5) based on the number of stocks held at the beginning of every formation period. We then compute *HM*, *BHM*, and *SHM* across all years separately for each quintile (with Q1 including the smallest funds) to evaluate whether herding depends on the number of stocks held by a fund. In our fund sample, funds with a German equity perspective on average held 43 stocks, funds with European equity focus 65 stocks, and funds investing in equities worldwide 82 stocks across the 10-year investigation period. Therefore, the number of stocks held seems to depend on the size of the stock universe from which a fund manager chooses his portfolio holdings.

[22] However, as Walter and Weber (2006) only analyze 60 equity funds primarily investing in German stocks, their fund sample is much smaller and more homogenous.

We display the results for the size subgroups in Panel B. Again we find the highest levels of herding among the largest funds (i.e. funds with the highest amount of stocks, grouped in Q5: *HM* of 5.58%). With a growing portfolio, managers need to gather information about more stocks and less time can be spent on analyzing individual equities (Jacob et al., 1999). Signals inferred from other big funds' trades might become more important and informational cascades may develop (Bikhchandani et al., 1992). Moreover, reputation-based herding (e.g. Scharfstein and Stein, 1990) might play a more important role for managers of large equity funds than for managers responsible for fewer assets.

3.4 Herd behavior of individual mutual funds

3.4.1 Do some funds herd more strongly than other funds?

Analyzing the herd behavior of individual funds is interesting for three reasons. First, fund managers might differentiate between buy-herding and sell-herding and thus show different directional herding levels. Second, if a fund exhibits similar herding intensities within a given and a succeeding period, it is likely that the degree to which the fund manager trades in accordance with the herd is the result of an intentional decision (e.g. Bikhchandani and Sharma, 2001). Third, by dividing the fund sample into subgroups of individual herding levels, we can analyze the impact of herding strategies on fund performance.[23]

Within every formation period, we calculate the individual herding measures introduced in Section 2 for every mutual fund active in the given period. Further, we allocate every fund to a quintile according to its cumulated level of $HM_{F,t}$, to a quintile according to its $BHM_{F,t}$, and to a quintile according to its $SHM_{F,t}$ at the end of each formation period. The funds belonging to the quintile with the highest (lowest) herding levels are grouped in quintile H5 (H1).

Panel A of Table 6 shows the distribution of the buy-side and sell-side herding quintiles within the single funds in a given period. If the funds' affiliation to a certain *BHM* quintile does not affect their affiliation to a certain *SHM* quintile, the funds of a given *BHM* quintile should be equally distributed across all *SHM* quintiles, i.e. 20% in each quintile. For the lowest *BHM* quintile (H1), we find that 6% more funds than expected in an equally distributed allocation belong to the quintile including the strongest sell-side "herders" (*SHM* quintile H5). Moreover, 27% of the funds that exhibit the strongest buy-herding tendencies (*BHM* quintile H5) are found in the lowest *SHM* quintile (H1). Apparently, managers that

[23] So far, other studies have mostly focused on the impact of institutional stock herding on stock performance. See for example Wermers (1999), Wylie (2005), and Walter and Weber (2006).

exhibit significant buy-side herding do not seem to herd with the same intensity when selling stocks and vice versa.

Insert Table 6 about here.

Panel B of Table 6 presents the relationship between funds' directionless herding quintiles in a given and in the next period. Again, if the funds' affiliation to a certain *HM* quintile does not affect their affiliation to a certain *HM* quintile in the next period, the funds of a given *HM* quintile should be equally distributed across all *HM* quintiles in the next period, i.e. 20% in each quintile. For the modest herding funds of the quintiles H2 to H4 we find 3% more funds than expected to be in the same quintile again in the next period. Of the funds that either do not herd at all (H1) or herd most significantly (H5) within a given period, we find 33% of them to be in the same extensive quintile again in the next period. Panel C and D of Table 6 display the relationships of the funds' directional herding quintiles in a given and in the next period. The two matrices show similar correlations of the funds' affiliation to specific herding quintiles in two consecutive periods. Further, we can statistically reject the null hypothesis that the distribution within the matrix is independent for all four matrices. The detected relationship between a fund's herding intensity in a given and the succeeding period indicates that fund herding is not the result of random trading decisions. In fact, managers seem to successively follow similar, more or less extensive, herding strategies across different periods.

3.4.2 Do herding strategies effect fund performance?

Grinblatt et al. (1995) find that fund performance is significantly correlated with the funds' herd behavior.[24] To analyze the impact of different, more and less intense herding strategies on fund performance, we calculate the funds' Sharpe ratios for each six-month formation period.[25] The Sharpe ratio is defined as the ratio of a fund's F average monthly rate of return, $\mu(R_{F,t})$, in excess of the risk-free rate $R_{f,t}$, to its absolute risk (the standard deviation of the return) in formation period t:

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24 Further, Grinblatt et al. (1995) show that on average well performing funds tend to herd by buying past winning stocks.

25 Eling and Schuhmacher (2007) show that the choice of performance measure does not affect performance rankings of hedge funds and that the Sharpe ratio is adequate to evaluate hedge funds.

$$Sharpe\ ratio_{F,t} = \frac{\mu(R_{F,t}) - R_{f,t}}{\sigma(R_{F,t})} \quad . \tag{5}$$

We measure the risk-free rate by the one-month EURIBOR and average the Sharpe ratios within each fund quintile of directionless herding and directional herding (H1 to H5).

Panel A of Table 7 displays the mean Sharpe ratios for the fund quintiles of directionless herding levels. Within a given period, those funds that trade most of their stocks in accordance with the trades of others perform best. We find an average Sharpe ratio of 0.126 for the strongest herding funds (quintile H5) and a ratio of only 0.077 for the least herding funds (quintile H1).

In addition, Panel B shows that funds exhibiting the highest levels of buy-herding (quintile H5) perform significantly better than funds that herd less. The average risk-adjusted performance increases monotonously in line with the buy-herding quintiles and the strongest buy-herding funds reveal a Sharpe ratio of 0.214 on average.

Panel C illustrates that on the sell-side, the relationship is reversed: the best-performing funds can be found within the lowest herding quintile (H1; average Sharpe ratio of 0.154). It seems that the optimal herding strategy for funds is, on the one hand, to buy stocks with the herd and, on the other hand, not to sell their stocks when others do. From Panel A of Table 6 we know that 27% of the funds that exhibit significant levels of buy-herding (quintile H5) actually do not herd when selling their stocks and belong to the lowest sell-side herding quintile (H1).

Insert Table 7 about here.

In unreported results, we compare the funds' returns (not risk-adjusted) with a market benchmark, the MSCI World Index.[26] When averaging the market adjusted excess returns within each fund quintile of directionless herding and directional herding, we find a relationship that confirms our results from above. On the one hand, the strongest buy-herding funds beat the market by 5.38% and the least sell-herding funds by 3.57% on average. On the other hand, the least buy-herding funds and the most sell-herding funds cannot outperform the market benchmark.

[26] We use the return of the MSCI World Index as benchmark since our sample includes stocks from different countries all around the world.

4 Conclusion

This paper investigates if equity fund managers in Germany act as a herd in their stock trades and if herding has an impact on fund performance. We find an overall herding measure of 4.28% which is rather modest in comparison to results from other European countries. We assume that a large part of the detected herd behavior might be triggered by funds belonging to the same mutual fund company and thus receiving the same research reports. With herding measures that vary quite significantly across the five biggest investment companies, we detect high levels of herding between 4.78% and 8.30% within the fund families. However, we also find statistically significant levels of herding across different mutual fund families.

Looking at managers' herd behavior beyond a purely national stock environment, we find an increased tendency of institutional investors to herd if the range of stock alternatives is vast. As a result, we detect the highest herding measures among funds with a global equity perspective when segregating the fund universe by geographic investment focus. Consistent with the theoretical literature, we expect large funds to be more reluctant to follow trades of their peers due to advanced research resources. Further, young fund managers in charge of small funds should be less willing to deviate from consensus portfolios out of reputational reasons. While we can empirically confirm the latter prediction, our results also show significant levels of herding among the biggest funds.

To analyze the impact of herding on fund performance, we introduce a simple refinement of the LSV measure of herding which allows us to assign herding levels to individual funds at the end of each formation period. We find the strongest buy-herding funds to perform significantly better than funds that herd less. On the sell-side however, we find the best-performing funds within the group of the least herding funds. As a matter of fact, 27% of the funds that exhibit the strongest levels of buy-herding actually do not herd when selling their stocks. We further identify 33% of the funds that herd least and 33% of the funds that herd most to show similar levels of herding again in the next period.

The detected tendency of German institutional investors to herd more within an international stock universe than in the national stock market leaves room for future research. By including different European institutional investors to the fund sample, one could, for example, analyze whether this tendency also holds true within other countries. Moreover, the significant herding levels inside mutual fund management companies should be observed more accurately. As our explanations are based on assumptions, a broad survey of the leading investment companies could shed more light on this topic.

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Table 1

The equity fund holdings database

Below, we present the key statistics of our database at two-year intervals. The mutual fund holdings database includes portfolio holdings data reported semi-annually from 01 January 2000 to 31 December 2009. The information below is reported for the end of the years and holdings of funds that report in September are considered as being reported in December. The trading statistics in the last panel are only inferred from trades within the last semi-annual formation period of the year. Panel A shows the number of funds included in our sample. Further, Panel B presents the total net equity assets of the average fund and the total equity value of all funds. Panel C displays the average number of stocks held per fund at the end of the respective year. Finally, Panel D includes the total number of trades, the buy-ratio of these trades, and the trading frequency which is the proportion of the total number of stocks traded to the total number of stocks held across all funds within that period. The values in the last column of the table show the averages calculated across all years and all reporting dates, including March and June.

	Year					
	2001	**2003**	**2005**	**2007**	**2009**	**Average**
Panel A. Fund counts						
Number of funds in database	555	681	684	754	715	654
Panel B. Equity values of funds						
Mean equity value of funds (€ million)	208.5	164.5	242.7	282.7	258.2	274.1
Total equity value of funds (€ billion)	115.7	112.1	166.0	213.1	184.6	144.0
Panel C. Stock counts						
Average number of stocks held per fund	52	58	64	67	79	61.8
Panel D. Trading statistics						
Total number of trades	14,993	31,015	34,981	44,970	52,806	32,146
Proportion of trades that are buys (%)	52.1	54.1	50.8	46.1	51.6	50.2
Trading frequency (%)	69.5	82.3	85.7	88.1	93.2	83.3

Table 2

Overall herding measures and results of other studies
(*HM* and median)

In Table 2, we calculate the average LSV measure of herding (*HM*) and the median across all $HM_{i,t}$ traded by at least two and five funds within our equity fund sample. The table also includes the number of stock-periods used to compute the measures and displays results of other studies for the purpose of comparison. Panel A shows the results across our whole fund sample. Due to the large sample sizes, all t-statistics are highly significant. Besides the results of the other studies, Panel B also includes the country of the analysis, the frequency of the respective holding data, and the period observed. Please note that for comparison, we display results for the lowest frequency when different frequencies of reporting dates were observed.

				At least two funds trading stock *i* in period *t*			**At least five funds trading stock *i* in period *t***		
LSV measure of herding				Mean (*HM*)	Number of stock-periods	Median	Mean (*HM*)	Number of stock-periods	Median
Panel A. Results across the whole fund sample									
All funds in database				0.0428	(79,774)	0.0326	0.0389	(32,358)	0.0174
Panel B. Results of other studies	Country	Frequency	Period						
Lakoniskok et al. (1992)	USA	Quarterly	1985-89	0.0270♣	-	0.0010♣			
Grinblatt et al. (1995)	USA	Quarterly	1975-84	0.0250♣	(41,905)		0.0432	(15,674)	
Wermers (1999)	USA	Quarterly	1975-94				0.0340	(109,486)	
Wermers (1999)	USA	Semi-annually	1975-94				0.0510	-	
Wylie (2005)	UK	Semi-annually	1986-93	0.0260	(27,014)		0.0250	(10,522)	
Walter and Weber (2006)	Germany	Semi-annually	1998-2002	0.0511	(1,832)		0.0559	(839)	
Dorn et al. (2008)	Germany	Quarterly	1998-2000	0.0830	(3,288)	0.0700			
Kremer and Nautz (2011)	Germany	Quarterly	2006-2009				0.0229	(1,395)	
Lobão and Serra (2006)	Portugal	Quarterly	1998-2000	0.1244	(3,000)		0.1354	(2,902)	
Voronkova and Bohl (2005)	Poland	Semi-annually	1999-2002	0.2260♣	(484)				

♣ The results are based on the minimal trading restriction of at least one fund trading stock *i* in *t*.

Table 3

Herding within mutual fund management companies
(HM)

The table below includes the mean herding measures (HM) calculated for the five biggest mutual fund management companies and across all investment companies within our sample. Panel A displays the results for the five biggest companies in terms of number of funds. The calculations of the adjustment factor $AF_{i,t}$ and the expected proportion of buyers p_t are based only on trading among the funds of a given investment company. Panel B includes the average level of herding computed across all five companies. Finally, Panel C shows average LSV measures using the mutual fund company as measurement unit. We sum the holdings over all funds within one company at each reporting date. An investment company is considered a buyer (seller) of a given stock if the cumulated holdings increase (decrease) within a given stock-period. We average the LSV measures across different subperiods and display the number of investment companies employed to compute the measure. Due to the large sample sizes, all t-statistics are highly significant.

Panel A. Herd behavior within each of the five biggest mutual fund companies

Investment Company	**Number of Funds**	***HM***	**Stock-periods**
A	137	0.0830	(13,282)
B	105	0.0478	(9,565)
C	85	0.0498	(9,745)
D	53	0.0802	(7,935)
E	52	0.0592	(3,670)
Mean	86.4	0.0656	(44,197)

Panel B. Herd behavior across the five biggest mutual fund comapnies

	Number of Funds	***HM***	**Stock-periods**
	432	0.0513	(35,807)

Panel C. Herd behavior for mutual fund companies

Subperiods	**Number of Companies**	***HM***	**Stock-periods**
2000-2009	240	0.0192	(73,273)
2001-2003	148	0.0194	(15,475)
2004-2006	172	0.0179	(24,039)
2007-2009	165	0.0202	(33,387)

Table 4

Herding segregated by funds' geographic investment focus
(*HM*, *BHM*, and *SHM*)

In Table 4, we calculate all $HM_{i,t}$ within different subgroups of funds for all stock-periods traded by at least two funds. The number of stock-periods for the respective group is shown in parentheses below the herding measures. Panel A displays the results of the average LSV measure of herding (*HM*) and the directional herding measures (*BHM* and *SHM*) for funds with a German equity focus. *BHM* and *SHM* represent values of $HM_{i,t}$ conditional on $p_{i,t} > p_t$ and $p_{i,t} < p_t$. Panel B describes the herd behavior among funds with a European equity focus and compares *HM*, *BHM*, and *SHM* to the results of Panel A. Finally, Panel C includes the herding measures for funds with a global equity focus and compares the results to the results of the other two subgroups. The p-values from t-tests indicating the probability that the means of the two subgroups are equal are displayed in brackets below the differences. Due to the large sample sizes, all t-statistics are highly significant.

	HM	***BHM***	***SHM***
Panel A. Herd behavior among funds with a German equity focus	0.0255	0.0265	0.0243
	(4,563)	(2,334)	(2,229)
Panel B. Herd behavior among funds with a European equity focus	0.0412	0.0457	0.0363
	(19,580)	(10,095)	(9,485)
Difference to			
funds with a German equity focus	0.0157	0.0192	0.0120
	[0.0000]	[0.0000]	[0.0016]
Panel C. Herd behavior among funds with a global equity focus	0.0497	0.0482	0.0512
	(24,485)	(12,324)	(12,161)
Difference to			
funds with a German equity focus	0.0242	0.0217	0.0269
	[0.0000]	[0.0000]	[0.0000]
funds with a European equity focus	0.0086	0.0025	0.0149
	[0.0000]	[0.2918]	[0.0000]

Table 5

Herding segregated by fund size
(*HM*, *BHM*, and *SHM*)

This table shows the mean herding measures (*HM*) as well as the directional herding measures (*BHM* and *SHM*) calculated for different fund subgroups segregated by fund size. *BHM* and *SHM* represent values of $HM_{i,t}$ conditional on $p_{i,t} > p_t$ and $p_{i,t} < p_t$. In Panel A we approximate the fund size by a fund's net equity assets. At the beginning of each formation period, every fund is assigned to a size quintile, with the smallest funds belonging to quintile Q1 and the largest funds to quintile Q5. The number of stock-periods for the respective group is shown in parentheses below the herding measures. The calculations of the adjustment factor $AF_{i,t}$ and the expected proportion of buyers p_t are based only on trading within each size quintile. In Panel B, we define the size of a fund by its number of stocks within the portfolio at the beginning of each formation period. Each fund is allocated to a size quintile at the beginning of each formation period. Again, $AF_{i,t}$ and p_t are calculated separately for each size quintile. We also show differences in means for both panels in the last column. The p-values from t-tests indicating the probability that the means of the two extreme quintiles are equal are displayed in brackets below the differences. All t-statistics are, unless the means are marked, significant at the 1% level.

Fund size quintiles:	**Q1 (small funds)**	**Q2**	**Q3**	**Q4**	**Q5 (large funds)**	**Differences in means Q5 minus Q1**
Panel A. Herd behavior among funds segregated by their equity value						
HM	0.0414	0.0221	0.0287	0.0350	0.0568	0.0155
	(1,933)	(2,990)	(4,451)	(6,551)	(7,188)	[0.0018]
BHM	0.0512	0.0155	0.0200	0.0374	0.0497	-0.0015
	(918)	(1,470)	(2,322)	(3,309)	(3,859)	[0.8226]
SHM	0.0325	0.0285	0.0383	0.0326	0.0651	0.0327
	(1,015)	(1,520)	(2,129)	(3,242)	(3,329)	[0.0000]
Panel B. Herd behavior among funds segregated by the number of stocks held						
HM	0.0408	0.0188	0.0409	0.0371	0.0558	0.0150
	(1,055)	(1,901)	(3,235)	(5,590)	(15,586)	[0.0188]
BHM	0.0495	0.0058†	0.0304	0.0410	0.0641	0.0146
	(513)	(984)	(1,721)	(2,840)	(7,862)	[0.1018]
SHM	0.0325	0.0328	0.0529	0.0331	0.0473	0.0148
	(542)	(916)	(1,514)	(2,750)	(7,724)	[0.1048]

† Mean herding measure statistically not significant.

Table 6

Distribution of directionless and directional fund herding quintiles

This table shows herding intensities of individual funds. We assign levels of directionless and directional stock herding to individual funds according to their trading activity within a given period. A fund that buys (sells) a stock *i* within a given period is assigned the stock's $HM_{i,t}$ and, if the stock was more (less) often bought than expected, the stock's $BHM_{i,t}$ ($SHM_{i,t}$) of the respective period. Thereby, each stock herding measure is weighted by the proportion of its trading value to the fund's total trading value within the given period. In every period, we then calculate individual herding intensities for each fund by cumulating its weighted stock herding measures. Every fund is assigned to a quintile according to its cumulated level of *HM*, to a quintile according to its *BHM*, and to a quintile according to its *SHM* at the end of each formation period. The funds belonging to the quintile with the highest (lowest) herding levels are grouped in quintile H5 (H1). Panel A shows the distribution of the buy-side and sell-side herding quintiles within the single funds in a given period. Panel B presents the relationship between the funds' directionless herding quintiles in a given and in the next period. Panel C and D display the relationships of the funds' directional herding quintiles in a given and in the next period. We perform chi-square tests and can statistically reject the null hypothesis that the distribution within the matrix is independent for all four matrices, for a significance level of 1%.

Panel A. Allocation of buy-side and sell-side herding quintiles

	Quintile of *SHM*					
Quintile of *BHM*	H1	H2	H3	H4	H5	Total
H1	0.19	0.17	0.19	0.19	0.26	1.00
H2	0.17	0.20	0.21	0.21	0.20	1.00
H3	0.16	0.22	0.23	0.22	0.18	1.00
H4	0.21	0.22	0.21	0.21	0.15	1.00
H5	0.27	0.21	0.19	0.18	0.15	1.00

Panel B. Allocation of directionless herding quintiles in a given and in the following formation period

	Quintile of *HM* , next formation period					
Quintile of *HM*	H1	H2	H3	H4	H5	Total
H1	0.33	0.21	0.15	0.15	0.16	1.00
H2	0.20	0.23	0.24	0.18	0.14	1.00
H3	0.16	0.23	0.23	0.22	0.16	1.00
H4	0.15	0.20	0.21	0.23	0.20	1.00
H5	0.15	0.13	0.17	0.22	0.33	1.00

Panel C. Allocation of buy-side herding quintiles in a given and in the following formation period

	Quintile of *BHM* , next formation period					
Quintile of *BHM*	H1	H2	H3	H4	H5	Total
H1	0.31	0.24	0.18	0.14	0.13	1.00
H2	0.23	0.23	0.21	0.18	0.14	1.00
H3	0.17	0.22	0.23	0.22	0.16	1.00
H4	0.14	0.18	0.23	0.25	0.20	1.00
H5	0.14	0.14	0.17	0.22	0.33	1.00

Panel D. Allocation of sell-side herding quintiles in a given and in the following formation period

	Quintile of *SHM* , next formation period					
Quintile of *SHM*	H1	H2	H3	H4	H5	Total
H1	0.29	0.20	0.18	0.17	0.17	1.00
H2	0.21	0.25	0.21	0.18	0.15	1.00
H3	0.14	0.23	0.23	0.22	0.18	1.00
H4	0.15	0.18	0.23	0.22	0.22	1.00
H5	0.18	0.14	0.17	0.23	0.28	1.00

Table 7

Average Sharpe ratios for directionless and directional fund herding quintiles
(Sharpe ratio)

Table 7 presents the average Sharpe ratios for the directionless and directional fund herding quintiles. We assign levels of directionless and directional stock herding to individual funds according to their trading activity within a given period. A fund that buys (sells) a stock *i* within a given period is assigned the stock's $HM_{i,t}$ and, if the stock was more (less) often bought than expected, the stock's $BHM_{i,t}$ ($SHM_{i,t}$) of the respective period. Thereby, each stock herding measure is weighted by the proportion of its trading value to the fund's total trading value within the given period. In every period, we then calculate individual herding intensities for each fund by cumulating its weighted stock herding measures. Every fund is assigned to a quintile according to its cumulated level of *HM*, to a quintile according to its *BHM*, and to a quintile according to its *SHM* at the end of each formation period. The funds belonging to the quintile with the highest (lowest) herding levels are grouped in quintile H5 (H1). We calculate the funds' Sharpe ratios within every formation period. We average the ratios within each fund quintile of directionless and directional herding. Panel A displays the mean Sharpe ratios of the fund quintiles of directionless herding levels. Panel B and C show the mean Sharpe ratios of the fund quintiles of directional herding levels. We present the differences in means of the two extreme quintiles in the last column of all three panels. Time-series t-statistics are computed and presented in parentheses below the mean Sharpe ratios.

Fund Herding quintiles:	**H1 (low levels)**	**H2**	**H3**	**H4**	**H5 (high levels)**	**Differences in means H5 minus H1**
Panel A. Average Sharpe ratio during formation period among funds segregated by their directionless levels of herding						
Sharpe ratio	0.0771	0.0895	0.0856	0.1085	0.1260	0.0489
	(5.43)	(6.46)	(5.95)	(7.48)	(8.23)	(2.34)
Panel B. Average Sharpe ratio during formation period among funds segregated by their levels of buy-side herding						
Sharpe ratio	0.0426	0.0642	0.0840	0.1032	0.2140	0.1714
	(3.00)	(4.69)	(5.71)	(6.57)	(13.55)	(8.07)
Panel C. Average Sharpe ratio during formation period among funds segregated by their levels of sell-side herding						
Sharpe ratio	0.1537	0.1124	0.1112	0.0805	0.0376	-0.1161
	(9.80)	(7.79)	(7.67)	(5.72)	(2.55)	(-5.39)