Kredit und Kapital, 45. Jahrgang, Heft 3, Seiten 343–371
Abhandlungen

Portfolio Complexity and Herd Behavior: Evidence from the German Mutual Fund Market

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I. Introduction

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/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)). Moreover, limited time capacities and information overload might lead professional managers to imitate trades of their peers.

A number of studies analyze the existence of herding strategies among money managers worldwide. Although most authors find evidence of herd behavior, at least to a certain extent, the results primarily hold for investments in national stocks of the country observed.[1] Furthermore, as most studies do not control for different fund characteristics, the results remain largely ambiguous, unpredictable, and country-specific. Cross-border investment funds, however, play a major role within the international fund industry.[2] For funds active in more than one specific country, the potential stock investments increase significantly and fund portfolios become more complex. For example, *Bolliger* (2004) finds that the degree

* An earlier version of the paper circulated under the title "Geographic Investment Focus and its Impact on Herd Behavior – Evidence from the German Equity Fund Market".

[1] See for example *Grinblatt* et al. (1995), *Wermers* (1999), *Walter/Weber* (2006), or *Kremer/Nautz* (2011).

[2] E.g., in the German mutual fund market, the market share of equity funds purely investing in German stocks accounts for only 11.8 % within our fund sample.

of international diversification of financial analysts' portfolios has a negative impact on forecast accuracy. Similarly, the information flood from various national stock markets might jeopardize a successful stock-picking strategy for money managers and herding strategies might become more attractive. The goal of this study is to investigate mutual fund herding within an international stock universe and to analyze the impact of portfolio complexity on herd behavior. Additionally, we introduce a simple and intuitive way to assign levels of herding to individual funds in order to analyze whether certain funds persistently herd more strongly than others.

According to *Bikhchandani/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 should also analyze information analogously. A further potential explanation of unintentional herding is that fund managers might follow fads (*Friedman* (1984)), causing significant stock herding within certain industries as funds herd into or out of a particular group of stocks.[3]

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." 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)). In contrast to this argument, we believe that nowadays managers often have to deal with an information overload, including conflicting signals. One

[3] However, if investing in accordance with fads is not triggered by correlated private information but rather reputational concerns or informational cascades, it must be classified as intentional industry herding, i. e. fund managers following each other into and out of the same industries (*Choi/Sias* (2009)).

way for managers to deal with the information flood is to disregard the private signals and instead trade in accordance with others.

In order to detect herding empirically, most studies employ a herding measure developed by *Lakonishok/Shleifer/Vishny* ((1992); hereafter the LSV measure). In brief, it measures the average tendency of a group of investors 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. With respect to herding by money managers, *Lakonishok* et al. (1992) find only weak evidence for herding among U.S. pension funds over the period from 1985 to 1989. *Grinblatt* et al. (1995) and *Wermers* (1999) identify statistically significant levels of herding for the U.S. mutual fund industry. 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 U.S. 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 moderate 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 regarding the largest stocks, i.e. herding out of stocks that recently performed well and into stocks with low returns.

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/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/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.[5]

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

[5] For herding studies across other market participants, such as financial analysts and exchange-rate forecasters, see for example *Bernhardt* et al. (2006), *Naujoks* et al. (2009), and *Pierdzioch* et al. (2011).

We base our analyses on the German equity fund market due to its popularity among private and corporate investors.[6] 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.[7] 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.[8] These numbers also underline the importance of professional asset managers' trading strategies for stock markets and investors.

Across the entire sample of equity funds, we find a LSV measure of 4.28 % for the 10-year observation period from 2000 to 2009. 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.

In accordance with our assumptions, we detect statistically significant higher levels of herding among managers that face a more complex investment task. We approximate a fund's portfolio complexity by its investment focus, the number of stocks held, and equity assets under management. Our analyses on herd behavior of individual funds reveal that significant buy-herding funds do not seem to herd with the same intensity when selling stocks and vice versa. In addition to that, we discover that within the two quintiles of funds that herd least and that herd most, 33 % of the funds show similar levels of herding again in the next period. Apparently, managers seem to follow similar extensive herding strategies across different periods.[9]

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[6] See *BVI-Investmentstatistik* (2011).

[7] Data provided by DAI (Deutsches Aktieninstitut e. V.).

[8] For comparison, the market capitalization of all German equities was about € 902 billion ($ 1,292 billion) at the end of 2009 according to DAI (Deutsches Aktieninstitut e. V.).

[9] If the detected herding was the result of random trading decisions, funds of a given herding quintile should be equally distributed across all herding quintiles in the next period, i. e. only 20 % in each quintile.

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 III introduces and interprets our empirical results of herding. Finally, Section IV concludes.

II. Data Sample and Methodology for Measuring Herding

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.[10] The FactSet mutual fund holdings database LionShares provides us with the global equity ownership data of the mutual fund portfolios. Our database contains the individual equity holdings of 1,181 equity funds on a semi-annual basis. 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 (German central bank).[11] 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/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

[10] 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.

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

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. Further, the sample is free of passively managed index funds as herding analyses are only meaningful if fund managers are not restricted in their purchase decisions. 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 the current 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. Finally, in order to avoid herding levels driven by new listings or delistings of stocks, we leave out stock-periods in which IPOs occur or stocks are being delisted. We receive the necessary data on capital actions, IPOs, and delistings from Datastream.

2. Descriptive Statistics

Table 1 shows a descriptive summary of our database. The number of funds included in our sample increases steadily from 2000 to 2007 and again rises from 2008 to 2009. The years presented in Panel A show an increase from 203 active funds in 2000 to 715 funds in 2009.[12] 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 analyses 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.

Panel B summarizes the net equity assets of our fund universe.[13] 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

[12] 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.

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

Table 1: **The Equity Fund Holdings Database**

Below, we present the key statistics of our database. 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 and the total number of stocks across all funds 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										
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average
Panel A. Fund counts											
Number of funds in database	203	555	634	681	682	684	725	754	705	715	654
Panel B. Equity values of funds											
Mean equity value of funds (€ million)	719.7	208.5	135.5	164.5	196.5	242.7	272.1	282.7	160.1	258.2	274.1
Total equity value of funds (€ billion)	146.1	115.7	85.9	112.1	134.0	166.0	197.3	213.1	112.8	184.6	144.0
Panel C. Stock counts											
Average number of stocks held per fund	52	52	53	58	60	64	65	67	68	79	62
Total number of stocks held by funds	2,865	4,719	4,787	5,406	5,856	6,333	7,049	7,815	7,675	7,726	6,114
Panel D. Trading statistics											
Total number of trades	1,839	14,979	23,018	30,997	31,491	34,970	36,881	44,961	44,553	52,795	32,132
Proportion of trades that are buys (%)	49.1	52.2	48.8	54.1	49.3	50.8	47.7	46.1	46.1	51.5	50.0
Trading frequency (%)	38.0	69.4	80.7	82.1	81.0	85.6	84.8	88.0	92.5	93.0	83.2

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.[14] 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 2000 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 32,132 trades within an average six-month trading period. Finally, we display the trading frequency of an average fund manager as proportion of stocks traded to stocks held. The trading rate increases to 93 % in 2009, with a mean of 83.2 % across the 10-year period.

3. Methodology

a) 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).[15] 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:

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

[14] 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.

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

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.[16] 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:

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

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.

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 trading 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.

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[16] As the counterparty of the respective trade can be any market participant, we might also observe periods with many funds purchasing (selling) and no fund selling (purchasing) a stock i. More precisely, $p_{i,t}$ would equal one (zero), if all funds observed were buying (selling) a given stock in a given period.

Although the LSV measure can be regarded as the standard measure for empirical herding studies, there also exist some drawbacks.[17] 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 buy-side of the stocks traded.

b) 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/Sharma* (2001)). We thus expand the measures presented above by applying them to individual funds in a simple and intuitive way.

We assign the calculated measures of directionless and directional stock herding to each individual fund F according to its trading activity within a given period t:

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

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.

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

Within every formation period, the calculated measure of directionless herding ($HM_{i,t}$) and, depending on whether the stock was more often or less often bought than expected, 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.[18] 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.[19]

III. Results

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.[20] 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 qualify as a herd. Table 2 also reports results for the restriction of at least five funds being active in a given stock-per-

[18] 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.

[19] *Grinblatt* et al. (1995) also develop a 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's buy herding and sell herding tendencies across time.

[20] See for example *Scharfstein/Stein* (1990), *Bikhchandani* et al. (1992), *Wylie* (2005), and *Walter/Weber* (2006). Raising the trading hurdle to 10, 25, or 50 funds active per stock-period, we still find statistically significant *HM* values around 4 %. However, to compare our results to prior research and to avoid the decreasing number of stock-periods, we stick with the restriction of at least two funds trading per stock-period.

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.

LSV measure of herding				At least two funds trading stock i in period t			At least five funds trading stock i in period t		
				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	79,730	0.0326	0.0388	32,351	0.0174
Panel B. Results of other studies	*Country*	*Frequency*	*Period*						
Lakoniskok et al. (1992)	USA	Quarterly	1985–1989	0.0270*	–	0.0010*			
Grinblatt et al. (1995)	USA	Quarterly	1975–1984	0.0250*	41,905		0.0432	15,674	
Wermers (1999)	USA	Quarterly	1975–1994				0.0340	109,486	
Wermers (1999)	USA	Semi-annually	1975–1994				0.0510	–	
Wylie (2005)	UK	Semi-annually	1986–1993	0.0260	27,014		0.0250	10,522	
Walter/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/Nautz (2011)	Germany	Quarterly	2006–2009				0.0229	1,395	
Lobão/Serra (2006)	Portugal	Quarterly	1998–2000	0.1244	3,000		0.1354	2,902	
Voronkova/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.

iod. 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 3.88 % (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.[21]

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 3.88 % 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/Weber* (2006) and *Kremer/Nautz* (2011) investigate the herd behavior among German institutions. While *Kremer/Nautz* (2011) only find a LSV measure of 2.29 %, *Walter/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 measures of 12.44 % among Portuguese mutual fund managers (*Lobão/Serra* (2006)) and 22.60 % among Polish pension fund managers (*Voronkova/Bohl* (2005)).

[21] Results based on higher trading hurdles are available upon request.

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/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/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.[22] 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.

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 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 invest-

[22] 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.

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 calculated 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	0.0829	13,281
B	105	0.0478	9,557
C	85	0.0498	9,741
D	53	0.0802	7,931
E	52	0.0592	3,670
Mean	86.4	0.0656	44,180

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

	Number of Funds	*HM*	Stock-periods
	432	0.0513	35,785

Panel C. Herd behavior of mutual fund companies

Subperiods	Number of Companies	*HM*	Stock-periods
2000–2009	240	0.0192	73,243
2001–2003	148	0.0193	15,455
2004–2006	172	0.0179	24,032
2007–2009	165	0.0202	33,384

ment 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. The Impact of Portfolio Complexity on Fund Herding

a) Herding Segregated by Funds' 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 and stocks 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/Weber* (2006)). *Wermers* (1999) argues additionally that in a heterogeneous universe of funds, a purchase by one fund is more likely to coincide with a sale by another fund. In unreported analyses, we therefore investigate herding intensities across different fund subgroups and stock subgroups.[23]

Because our database is not restricted to equity funds primarily investing in German stocks or specific industry stocks, we can approximate a fund's portfolio complexity by its investment focus. In the financial analyst literature, portfolio complexity is commonly determined by the number of companies and industries covered by an analyst (e. g. *García-Meca/Sánchez-Ballesta* (2006)). Accordingly, one way to determine the complexity of a fund manager's investment task is to separate equity funds focusing on single countries from cross-border equity funds focusing on multiple countries. As these funds 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. The search problem regarding stock purchases and the

[23] The results of these analyses are available upon request.

portfolio complexity in general increase in line with the number of stock alternatives.[24]

Jacob et al. (1999) assume that research analysts following a large number of companies might exhibit lower forecast accuracy, i. e. higher errors among the forecasted earnings, due to their reduced research focus. In contrast, one could also argue that a large stock universe covered should correlate with low forecast errors, as the most capable analysts are likely to be assigned larger numbers of companies. Furthermore, following several companies might provide an analyst with deeper insights into industry trends (*Jacob* et al. (1999)). In fact, *Jacob* et al. (1999) 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 empirical study, *Clement* (1999) documents that analysts' forecast accuracy is negatively associated with portfolio complexity, which he measures by the number of companies and industries followed by single analysts.

Bolliger (2004) states that even industry-specialized analysts face a more complicated task if they follow stocks across different countries. Similar to financial analysts, managers of funds focusing on multiple countries have to cope with different accounting practices and national effects such as foreign exchange, interest rates, and commodity price shocks. In combination with managers' limited time capacities and the information overload regarding the potential stock investments, these factors might lead managers to imitate trades of other funds causing high levels of herding.

The 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. If applicable, we sort the remaining funds into one of the following subgroups according to their BVI investment style: single-country focus (158 funds) and multiple-countries focus (110 funds).[25]

Table 4 presents directionless and directional herding measures for the respective subgroups. Panel A presents *HM* averaged across all funds

[24] *Barber/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.

[25] We allocate the remaining funds into these upper-level groups to assure a sufficient number of funds for the herding analyses. The single-country focus subgroup includes all funds investing in one specific country worldwide. The group of funds focusing on multiple countries includes equity funds investing in emerging markets, Far East, Far East including Japan, Latin America, and Eastern Europe.

Table 4

Herding Segregated by Funds' 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. *BHM* and *SHM* represent values of $HM_{i,t}$ conditional on $p_{i,t} > p_t$ and $p_{i,t} < p_t$. The calculations of the adjustment factor $AF_{i,t}$ and the expected proportion of buyers p_t are based only on trading within a given subgroup. 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. 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. Further, Panel C includes the herding measures for funds with a global equity focus and compares the results to the results of the prior two subgroups. Finally, Panel D and Panel E show the herding measures for the average single-country focused fund (excluding Germany) and the average multiple-countries focused fund (excluding the European and global equity focus). Due to the large sample sizes, all t-statistics of the means are highly significant. 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.

	HM	*BHM*	*SHM*
Panel A. Herd behavior among funds with a German equity focus	0.0253 (4,556)	0.0265 (2,329)	0.0241 (2,227)
Panel B. Herd behavior among funds with a European equity focus	0.0412 (19,573)	0.0457 (10,091)	0.0363 (9,482)
Difference to funds with a German equity focus	0.0159 [0.0000]	0.0192 [0.0000]	0.0122 [0.0013]
Panel C. Herd behavior among funds with a global equity focus	0.0497 (24,483)	0.0482 (12,322)	0.0512 (12,161)
Difference to funds with a German equity focus	0.0244 [0.0000]	0.0217 [0.0000]	0.0271 [0.0000]
Difference to funds with a European equity focus	0.0085 [0.0000]	0.0025 [0.2975]	0.0149 [0.0000]
Panel D. Herd behavior among funds with a single-country equity focus	0.0188 (22,409)	0.0194 (10,996)	0.0184 (11,409)
Panel E. Herd behavior among funds with a multiple-countries equity focus	0.0461 (12,472)	0.0593 (6,061)	0.0336 (6,411)
Difference to funds with a single-country equity focus	0.0273 [0.0000]	0.0399 [0.0000]	0.0152 [0.0000]

with a German equity focus. We find a herding measure significantly lower (*HM* of 2.53 %) 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/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)).

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 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. Higher buy-herding levels than sell-herding levels (4.57 % vs. 3.63 %) could be an indicator for attention-driven purchase decisions. In accordance with our predictions, Panel C reveals that funds with a global equity focus, i.e. funds with the most complicated investment task, exhibit the highest levels of herding amongst the subgroups (*HM* of 4.97 %).

To control whether the low herding measures within the single-country investment universe were specific for the German equity focused funds, we calculate the degree of herding across all remaining single-country focused funds (Panel D). Further, Panel E presents the herding results for all remaining funds focusing on multiple countries. Again, we find a statistically significant lower herding intensity (*HM* of 1.88 %) among the single-country focused funds than among the less focused funds (4.61 %). It seems as if the degree of herding is positively correlated to the complexity of the investment task, approximated by the size of the stock universe from which managers can choose their portfolios.

b) Herding Segregated by Fund Size

Another way to approximate portfolio complexity is by fund size: the larger a portfolio, the more complicated the manager's investment task.

We therefore segregate the funds by size in terms of both, number of stocks held and equity value. Again, we expect the degree of herding to increase in line with portfolio complexity. However, theoretical assumptions suggest that larger funds should be more reluctant to follow informational cascades (*Bikhchandani* et al. (1992)) due to an assumed high research disposal and capacity. As they receive more detailed information, they should be able to trust more on their private signals. Accordingly, in their empirical analysis, *Frey/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.

At the beginning of each formation period, we allocate every fund to a size quintile (Q1 to Q5) based on the number of stocks held (with Q1 including the smallest funds). We then compute *HM* across all years separately for each quintile. In our fund sample, funds with a German equity perspective on average held 43 stocks, funds with a European equity focus 65 stocks, and funds investing in equities worldwide 82 stocks across the 10-year investigation period.[26] To a certain extent, the number of stocks held seems to depend on the size of the stock universe from which a fund manager chooses her portfolio holdings.

Panel A of Table 5 shows the average herding measures segregated by size in each formation period. 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 5.57 %). With a growing portfolio, managers need to cope with more information about more stocks and less time can be spent on analyzing individual equities (*Jacob* et al. (1999)). This diffusion-of-focus effect seems to induce managers to imitate their competitors, also because herding equals less working effort (*Lütje* (2009)).

The alternative way to segregate funds by size is to allocate every fund to a size quintile (Q1 to Q5) based on the fund's net equity assets 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). Once more, our results in Panel B reveal that large funds seem to herd more than small funds and in particular more than medium-sized funds. The difference in means between the *HM* of the smallest

[26] The remaining single-country focused funds on average held 40 stocks and funds investing in multiple countries 34 stocks.

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 define the size of a fund by its number of stocks within the portfolio. 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 approximate fund size by a fund's net equity assets. 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 the number of stocks held						
HM	0.0408	0.0188	0.0409	0.0371	0.0557	0.0149
	(1,055)	(1,899)	(3,235)	(5,587)	(15,583)	[0.0191]
BHM	0.0495	0.0059*	0.0304	0.0409	0.0641	0.0146
	(513)	(984)	(1,721)	(2,839)	(7,861)	[0.1023]
SHM	0.0325	0.0328	0.0529	0.0332	0.0472	0.0147
	(542)	(916)	(1,514)	(2,748)	(7,722)	[0.1062]
Panel B. Herd behavior among funds segregated by equity value						
HM	0.0413	0.0221	0.0288	0.0350	0.0568	0.0155
	(1,930)	(2,988)	(4,446)	(6,548)	(7,188)	[0.0017]
BHM	0.0510	0.0155	0.0200	0.0374	0.0497	–0.0013
	(916)	(1,469)	(2,319)	(3,306)	(3,859)	[0.8506]
SHM	0.0325	0.0286	0.0383	0.0326	0.0651	0.0326
	(1,014)	(1,519)	(2,127)	(3,242)	(3,329)	[0.0000]

* Mean herding measure statistically not significant.

funds (4.13 %), stated in Q1, and the largest funds (5.68 %), stated in Q5, amounts to 1.55 % and is statistically significant at the 1 % level. With more assets to allocate, fund managers face an increased search problem regarding their stock investments. In addition to the increased portfolio complexity of larger funds, the detected herding might be triggered by funds belonging to the same, big mutual fund family and thus reacting to the same "private" signals derived from internal stock recommendations. These results oppose the observations of *Walter/Weber* (2006), who do not find an impact of fund size on herding in their fund sample.[27]

With respect to the smallest funds, we find higher levels of herding in Q1 compared to the three remaining groups, Q2 to Q4. Panel A and Panel B show this effect in particular for the detected buy-herding measures (*BHM*). If we assume that the smallest funds are usually managed by younger, inexperienced fund managers, reputation-based herding models (e. g. *Scharfstein/Stein* (1990)) could also explain high levels of herding within our smallest fund subgroup. Career concerns might give young professionals an incentive to herd (*Keynes* (1936)). As a matter of fact, *Chevalier/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.

4. Herd Behavior of Individual Mutual Funds

Analyzing the herd behavior of individual funds is interesting for two 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/Sharma* (2001)).

Within every formation period, we calculate the individual herding measures introduced in Section II.3.b 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.

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

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 of 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

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 of 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

(Continue next page)

Table 6: Continued

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

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

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.

IV. Conclusion

This paper investigates if equity fund managers in Germany act as a herd in their stock trades and if portfolio complexity has an impact on herd behavior. 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 8.29 % within the fund families. However, we also find statistically significant levels of herding across different mutual fund families.

We approximate the complexity of a fund's investment task by its investment focus, the number of stocks held, and assets under management. Thereby, we find institutional investors to herd more extensively when they invest in stocks from more than one country. It seems as if the degree of herding is positively correlated to the number of potential stock investments. As a result, we detect the highest herding measures among funds with a global equity focus, i. e. the most complex investment focus.

The bigger a fund, the more complicated the investment task, as managers need to cope with more information about more stocks. For both fund size measures – stocks held and assets under management – we find the highest herding levels among the biggest funds. The associated information overload seems to induce managers to imitate each other's trades.

Finally, 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. Apparently, managers differentiate between buy-herding and sell-herding strategies. We detect that 27 % of the funds that exhibit the strongest levels of buy-herding actually do not herd when selling their stocks. We further identify a certain persistence regarding managers' herding intensities: 33 % of the funds that herd least and 33 % of the funds that herd most show similar levels of herding again in the next period.

The detected tendency of German money managers to herd more if they face a more complicated investment task 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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Summary

Portfolio Complexity and Herd Behavior: Evidence from the German Mutual Fund Market

We examine the herd behavior among equity funds in Germany based on a large 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. In contrast to existing herding studies which analyze herd behavior within a purely national stock environment, we investigate mutual fund herding in international stocks. We contribute to the literature by analyzing the impact of portfolio complexity on herd behavior. We find the most pronounced levels of herding for funds choosing their portfolio stocks from a broad, international and therefore complex investment universe. Further, we approximate a fund's portfolio complexity by its size and find high levels of herding among the biggest funds. 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. We show that managers differentiate between buy-herding and sell-herding and that individual funds exhibit similar herding intensities within a given and a succeeding period. (JEL D82, G11, G23)

Zusammenfassung

Portfolio-Komplexität und Herdenverhalten: Erkenntnisse aus dem deutschen Investmentfonds-Markt

Wir untersuchen das Herdenverhalten von deutschen Aktienfonds anhand einer großen Fonds-Stichprobe für die Jahre 2000 bis 2009. Wir zeigen, dass ein großer Anteil des aufgezeigten Herdenverhaltens durch identische Handelsentscheidungen von Fonds der gleichen Investmentgesellschaft erklärt werden kann. Jedoch finden wir auch statistisch signifikantes Herdenverhalten bei Fonds von verschiedenen Fondsgesellschaften. Im Gegensatz zu existierenden Studien, die Herdenverhalten ausschließlich innerhalb nationaler Aktienmärkte analysieren, untersuchen wir auch das Herdenverhalten innerhalb internationaler Aktienmärkte. Wir erweitern die Literatur durch unsere Analysen hinsichtlich des Einflusses der Portfolio-Komplexität auf Herdenverhalten. Wir finden die höchsten Maße für Herdenverhalten für Aktienfonds, die in großen, internationalen und daher komplexen Märkten investieren. Des Weiteren approximieren wir die Portfolio-Komplexität durch die jeweilige Fondsgröße und entdecken eine starke Herden-Ausprägung bei den größten Fonds. Um das Herdenverhalten von einzelnen Fonds innerhalb verschiedener Perioden zu analysieren, führen wir eine neue und intuitive Methodik ein. So können wir zeigen, dass sich das Herdenverhalten der Fondsmanager bei Kauf- und Verkaufsentscheidungen unterscheidet und dass individuelle Fonds auch in der nächsten Periode ähnliche Herdenstrategien verfolgen.