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Do mutual funds specializing in German stocks herd?

1. The importance of institutional investors in the German stock market

An important topic addressed in financial market research as well as by practitioners is the structure of institutional investors´ information and decision processes and their consequences for market price movements. If one talks to money managers but also to financial economists in private conversation, most of them state that investors are influenced by the decisions of other investors: KEYNES's famous „beauty contest" is still alive in investment industry.

It is also widely acknowledged that the behavior of institutional investors such as banks, insurance companies, mutual and closed-end funds, and large (multinational) companies potentially influences stock prices. This influence on prices can be related directly on high volumes of buy or sell orders (see the studies by KRAUS/STOLL 1972, HARRIS/GUREL 1986, HOLTHAUSEN/LEFTWICH/MAYERS 1987 and CHAN/LAKONISHOK 1993) as well as indirectly on informational effects through the submission and execution of large orders. For real price impact the necessary condition of high trading volumes has to be complemented by the sufficient condition of an investment behavior in the same direction (herding). Herding is potentially most pronounced for the group of investment funds as LAKONISHOK/SHLEIFER/ VISHNY (1992, 26) pointed out: „Typically, money managers are evaluated against each other. To avoid falling behind a peer group by following a unique investment strategy, they have an incentive to hold the same stocks as other money managers."

Supposed that there is evidence for herding by investment funds then the question arises about the counterparties on the opposite side of the market. It is possible that other institutional investors as well as private investors (which have a much bigger share of total market volume compared to investment funds; cf. Figure 1 below) apply different time horizons for their investment strategies. These groups may therefore be acting as counterparties of the herd.

The following analysis concentrates on the question whether the behavior of German institutional investors exerts herding or not. Therefore, the study uses data on holding of nearly all German

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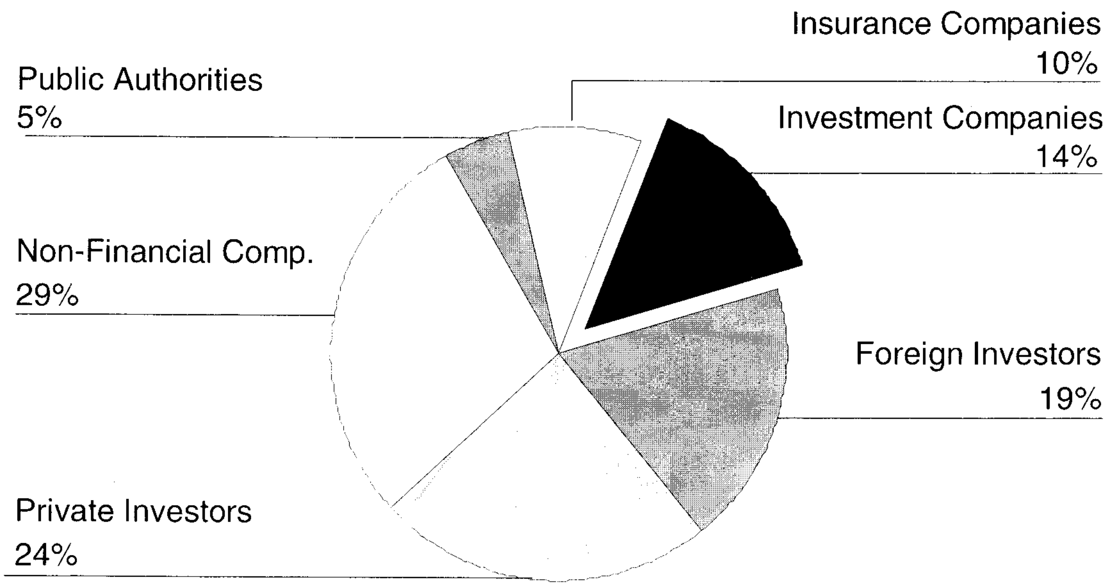
Figure 1: Investors in the German stock market



domestic stock open-end investment funds. These mutual funds are allowed to invest in the two market segments of the German Stock Exchanges, the official market („amtlicher Handel“) and the semi-official market („geregelter Markt“) (see § 8 KAGG, the investment companies act). In 1994 519 domestic stocks were listed on the former and 171 on the latter. The semi-official market only represents a proportion of 3% of the market capitalization of both segments.

To give a first impression of the role of investment funds in the German stock market, it is helpful to gauge the importance of some groups of investors in the market from data provided by the German Central Bank (Deutsche Bundesbank). Figure 1 presents the relative proportions of six groups of investors based on market values (deposit holdings in DM). Investment companies potentially may have a stronger position in the market than their 10% market share indicates because their analysts' forecasts influence the behavior of related banks and insurance companies and they have a high turnover ratio on their asset holdings.

The paper is organized as follows. The next section considers main reasons why fund managers might herd, gives an introduction to related work, and states the hypotheses for the empirical analysis. Section 3 presents the data, section 4 discusses the herding measures and the results of the study. Section 5 concludes.

2. Related work and hypotheses

2.1 Previous literature

There exists some theoretical literature that has analyzed herding of institutional investors in several contexts.

In a wider sense herding in financial markets means that behavioral patterns of investors are positively correlated. But this definition is too unprecise for an empirical study because it is impossible to distinguish whether herding stems from correlated information arrival of independently acting investors or from correlations across investors´ behavior (cf. DEVENOW/WELCH 1996, 604). So, most of the related studies use the term „herding“ to describe a behavior which leads to sub-optimal decision-making of all investors. Under a rational or semi-rational view, herding is caused by difficulties in the information acquisition or incentive issues in most of the models.

- Some studies deal with the assumption that money managers (investors) herd on *information acquisition*. This means that fund managers find it worthwhile to search for further information only if others in the industry do.
  The models of FROOT, SCHARFSTEIN and STEIN (1992) analyze investors with a short-term horizon who seek information held by other market participants. These investors ignore information about „the“ fundamental asset value and herd on a subset of information. This result is determined by the assumption that the traders with their two-period horizons receive the fundamental value only in the final period in a three-period world. The fundamental information may not be incorporated in the market prices before the end of the long-term horizon. The study shows that if traders are „endowed“ with short investment horizons, they herd on the same information, trying to learn what the informed investors know.
  Closely related work of HIRSHLEIFER, SUBRAMANYAM and TITMAN (1994) focuses on trading behavior when some market participants receive common price information before others. The main difference to the aforementioned model by Froot et al. is that all (informed) trading strategies are determined endogenously. HIRSHLEIFER et al. demonstrate that it is worthwhile for a first investor to acquire information in a stock because she can profit from this behavior with a minimum risk if she expects that other traders will soon discover the same information. Their model implies that investors will focus only on a subset of securities available in the market, while neglecting other alternatives with similar characteristics.
- A more recent study of MAUG and NAIK (1995) deals with a similar topic. But they focus on the link between information assumption, investment decisions, and the relative performance evaluation in delegated portfolio management (more closely to our subject). So, MAUG and NAIK shift their analysis in the context of *principal-agent relationships* under the general assumption that (strong) elements of relative performance evaluation are introduced into the compensation which the fund managers receive from the owners and trustees of the funds they manage.
  The study demonstrates that this may bias money managers to deviate from optimal asset allocations and follow those of their benchmarks (like a well known stock market index, e.g. the DAX) if the principal measures the efficiency of the fund manager´s information acquisition and investment decisions by making his compensation contingent on his performance relative to his peers in the industry. The authors conclude (p. 3): „... Fund managers neglect a part of their own information and adjust their portfolio allocation to that of other funds. This happens even if their own information is superior.“
  A former paper of SCHARFSTEIN and STEIN (1990) examines herding behavior in investment contexts and focuses on the reputation of money managers concerning the labor market (labor market´s inferences regarding their ability). Their model assumes two types of managers. One who receives „true“ information and another who receives purely noisy signals. While the labor market cannot identify both types initially, the labor market´s opinion is updated after the managers have made an investment decision based on two facts: whether the investor´s behavior leads to profitable invest-

ment and whether the behavior of the manager is similar to or different from that of others. The first aspect will not be used exclusively, since on any given draw the type 1 managers could be unlucky. Therefore, the second fact is important, too. The authors conclude that if holding the absolute profitability fixed, the type 1 investors will be more favorably evaluated if they follow the crowd. „Thus an unprofitable decision is not as bad for reputation when others make the same mistake ...“ (p. 466). Concerning financial markets SCHARFSTEIN and STEIN suggest that the asset allocation decisions of *professional money managers should be more closely correlated over the time than the decisions of equally active private investors who are unconcerned about their reputations.* This conclusion motivates our own study with German money managers.[1]

The findings of SCHARFSTEIN and STEIN were completed and extended by some other papers in the context of security analyst´s recommendations and forecasts. A study by STICKEL (1990) demonstrates that herding on earnings intensifies as the number of estimates close to the consensus increases and the quality of one´s prior forecasts decreases (see also STICKEL 1992 and 1995, COTE/SANDERS 1995 for the influence of the analyst´ s reputation).

TRUEMAN (1994) concludes that it is optimal for late moving security analysts to copy earlier colleagues, even when both are provided with the same information, and even when this is not justified by their information.

OLSEN (1996) suggests that the human desire for consensus leads to herding behavior among earnings forecasters. This leads to a reduction in the dispersion and an increase in the mean of the distribution of expert forecasts and creates a positive bias and inaccuracy in published earnings estimates.

- A third group of recent papers addresses the more general explanation that herding behavior can occur when investors make use of private information at the time that they decide whether or not to conform or deviate. On principle, the story goes that investors gain useful information from observing previous decisions of investors, with the possible consequence that they completely ignore their own private information (*informational cascade model*).

  While the paper of WELCH (1992) examines the likelihood of cascades and optimal pricing in the IPO market, BANERJEE´s (1992) study models more independently herding as cascades.

  The paper of BIKHCHANDANI, HIRSHLEIFER and WELCH (1992, henceforth, BHW) focuses on the fragility of cascades with regard to different market situations, in particular.

  The more recent empirical paper of WELCH (1996) documents that one recommendation of an analyst has a significant influence on the recommendation of the next analyst. WELCH also finds evidence that herding towards the consensus is probably not caused by fundamental information which is consistent with the models of WELCH (1992) and SCHARFSTEIN/STEIN (1990). With regard to the BHW analyses, the WELCH study indicates that up-market situations may be more „fragile“ than down-markets. Welch explains these findings with the interpretation that up-markets may aggregate less information.

- Only a few papers attempt to analyze the herding phenomenon *empirically.* With exception of some empirical studies concerning analyst´s recommendations we are aware of three papers related to our research topic, the mutual funds. WERMERS (1994) and GRINBLATT, TITMAN and WERMERS (1996, henceforth, GTW) examine herding from the view of investment funds and not from the perspective of individual stocks. They link their results of funds´ herding to their finding of momentum-based strategies. They present evidence that mutual funds have a tendency to buy stocks on their past returns (buying past winners and selling past losers), and the tendency to buy and sell the same stock at the same time (invest with the herd) in excess of what they expected from pure chance (statistically significant, but not particularly large) (see the similar results in the paper by FALKENSTEIN 1996).

The similar paper of LAKONISHOK, SHLEIFER and VISHNY (1992, henceforth, LSV) finds only a small correlation in trading activity overall, except for small stocks. They use end-of-quarter portfolio holdings of US pension funds. The LSV measure is quite similar to the measure of the GTW study. It defines herding for a given stock in a given period, H(i), as

$$H(i)=\left|\frac{B(i)}{B(i)+S(i)}-p(t)\right|-AF(i) \qquad (1)$$

where B(i) is the number of money managers who increase their holdings in the stock in the period (net buyers), S(i) is the number of money managers who decrease their holdings (net sellers), p(t) is the expected proportion of money managers buying in that period relative to the number active, and AF(i) is an adjustment factor which is needed for the subtraction of p(t) and the integer-valued number of fund managers.

This herding measure causes some problems for its interpretation:

- The ratio B(i)/(B(i)+S(i)) amounts to zero in the case of no herding. But the ratio also amounts to zero if all money managers are on the sell-side of the market. The latter also has to be interpreted as herding behavior. Therefore, the interpretation of the outcomes of the ratio are ambiguous.
- The correction with p(t) represents a conservative procedure.[2] The subtraction of p(t) eliminates herding behavior of the population across all stocks. LSV do not capture market-wide herding. The remaining behavior looks like a stock-picking herding or excess-buying which occurs if money managers invest more cash inflows in a single stock relative to the market.

With regard to the goal of their study, i.e. looking at the possible impact of institutional trading on price movements, the p(t) adjustment leads to a lack of information because the averaging procedure (across all stocks) does not allow to compare stock by stock separately. The adjustment for variation in net buying in every period due to client cash inflows does not take into consideration that a money manager is not obliged to invest the inflows in the same stocks in the same period as other managers do. But if most of the fund managers try to invest cash inflows quickly and in the same bundle of stocks (e.g. blue chips or the index stocks), herding behavior occurs.

In other words, it is necessary to distinguish between *two types of herding behavior*, the aforementioned *excess* or stock-picking *herding* and the latter one which we call market-wide or *benchmark herding* with regard to the theoretical literature cited above (concerning the agency and the relative performance explanation). The LSV study only concentrates on the excess herding and eliminates benchmark herding.[3]

- ❑ Finally, a group of papers discusses herding from a behavioral science point of view, concerning issues like investor psychology, behavioral finance, near or bounded-rational, and non-rational models. One of the most influencing studies is the paper by SHILLER and POUND (1989) who use questionnaire surveys of institutional and individual investors. The authors present a contagion or epidemic model of financial markets in which interest in individual stocks is spread by word of mouth especially in markets with stocks whose prices have recently increased dramatically. They find that among institutionals the interest in a stock was more likely to be influenced by other individuals or publications than by a systematic search (see the survey article of SHILLER 1990, too).

  A more recent study of LUX (1995) contributes to this kind of literature. The analysis incorporates psychological factors that determine the behavior of non-rational traders explicitly.

LUX assumes that the expectation formation of investors who are not fully informed about fundamentals depends mainly on the behavior and expectations of others. The study explains the emergence of bubbles as a self-organizing process of infection among investors. The author postulates that the traders' readiness to follow the herd depends on the actual returns. He suggests that above average returns are reflected in a generally more optimistic attitude that contributes to the disposition to adopt others´ (bullish) beliefs and vice versa (see also the experimental work of PINGLE (1995) in another decision context).

2.2 Hypotheses

A first approach to analyze whether fund managers potentially herd relates to the number of managers. We look at a given stock in a given time period (see the data section below) and compute the change in holdings for each mutual fund. Thus, we can explore whether fund managers tend to end up on the same side of the market, i.e. whether a disproportionate number of managers are selling or buying this stock; the benchmark is virtually the equal distribution (50% sellers, 50% buyers; see section 4.2 below). So, we define trades on the same side of the market as sufficient condition for a potential price impact.

As pointed out in the introduction the necessary condition for a potential price influence of institutionals is their (high) trading volume. So, we have to analyze the direction of trading volume of all money managers active in a given stock, too. Only if the volume signals an excess demand or supply, i.e. the net traded volume on one side of the market, price impact might occur. Because of the data (see below) we use the changes in holdings (flows) between two time periods as proxy for trading volume.

With reference to these first considerations we state the following hypotheses:

- Concerning the LSV study we expect that no excess (or stock-picking) herding occurs in the data (*Hypothesis 1*).
- In contrast to LSV and with regard to the theoretical literature cited above, in particular the agency models of herding, we hypothesize that benchmark herding can be explored in the mutual funds´ behavior (*Hypothesis 2*).
- Corresponding to the LSV paper and to the theoretical literature concerning the information acquisition and cascade models we expect that small caps are more afflicted by herding than other stocks (*Hypothesis 3*).
- In addition, we analyze whether herding behavior differs between industries.

LSV state for their data set that it is „not ideal for analyzing the impact ... on prices. Our quarterly data do not enable us to distinguish between the impact of trades on prices and within-quarter trading strategies that respond to within-quarter price moves“. In our data (see below) we have the same restriction, too. It is not possible to get trading data with higher frequency to analyze the behavior of institutionals and contemporaneous price movements for e.g. the last decade. But we believe that it is worthwhile to look only at middle-term holding changes and estimate from this whether herding occurs in the German domestic stocks funds sector or not (see some suggestions for future work below).

3. Data

The analysis is based on end-of-half-year portfolio holdings of 28 German open-end domestic stock mutual funds, which represent about 91 percent of the competitors' assets (estimated by the BVI (German Association of Investment Companies 1993, 27–39); 100 percent is equal to 11.9 Billion DM asset value in 1992).[4] The data collected for the period from 1988 to mid 1993 include the mutual funds of the five largest investment companies in Germany.

A minor group of the sample's mutual funds reports do not coincide with the calendar year. Therefore, mutual funds have to be separated into two groups for the analyses. One group has reporting dates at the end of March and September (11 funds of 7 companies) and the other has dates at the end of June and December (17 funds of 8 companies).

The proportion of active fund managers in a given period varies from a quarter to a third of all fund managers in the sample (active managers are managers of funds who sell or buy in a period). These managers increase or decrease about a quarter to a third of all 530 stocks held by the investment funds in each half-year (the maximum number of different stocks is 690, see above section 1). The activity level in each share that is traded in a period is about five fund managers or higher.

4. Herding – Measurement and results

4.1 Excess Herding

With regard to the LSV study we explore our data for stock-picking herding analogously to the measure defined in their paper (see above). While the measure´s value reported by LSV amounts to 0.027 the German equivalent amounts to 0.029. So, concerning our *Hypothesis 1* we do not find any significant excess herding behavior of the German mutual fund managers.

4.2 Benchmark Herding – Overall results

Following the arguments stated in the characterization of the LSV measure (see section 2.1) we have to consider a second measure to control for market-wide or benchmark herding behavior of the fund managers. Therefore, we define

$$HF(i)=\left|\frac{BF(i)-SF(i)}{BF(i)+SF(i)}\right| \tag{2}$$

where BF(i) is the number of fund managers who are net buyers of a stock i in a period, and SF(i) is defined analogously for net sellers (HF means herding of fund managers).

The ratio is adjusted to the number of *active* fund managers to prevent from artificial effects from funds with no net change in holdings. HF(i) would be 1 if all of the active fund managers buy (sell) the same stock in the same half-year period. The measure avoids the problem of the LSV measure because the difference of net buyers and net sellers in a given stock is calculated in the numerator.

But HF(i) lacks expressiveness because the number of money managers who invest on the same side of the market is only a weak indicator for the price impact of herding (this holds also true for the LSV measure). For example, half of the fund managers might be engaged on the sell side but the other half might be making the larger trades on the buy side, potential price movements would be expected from the latter. So, with regard to the goal of our study, the HF(i) ratio would give the wrong signal (no herding). As a consequence, we define a second measure of herding behavior

$$HV(i)=\left|\frac{BV(i)-SV(i)}{BV(i)+SV(i)}\right| \tag{3}$$

where BV(i) is the volume traded by net buyers of a stock i in a period, and SV(i) is defined analogously for net sales. Because of the data available in this analysis the volume is defined by the number of shares. For the analysis of herding it makes no difference if the number of shares or the DM volume is used (HV measures herding corresponding to the traded volume). HV(i) expresses the excess demand or supply in a given stock in a given half-year period.

Additionally both ratios can be characterized:

The integer value of the single stocks´ ratio is calculated to prevent compensatory effects between the ratios of two or more stocks in an averaging procedure, i.e. the computing of HV or HF for a group of stocks (e.g. an industry or small caps).

From the integer-value procedure follows that the measures´ value lies between zero and one (instead of the former range –1, +1), and no differentiation between sell-herding and buy-herding is possible. This lack of information is acceptable because the primary goal of the study is to estimate herding behavior and not the direction of it in particular.

The calculation of integer values makes it necessary to define a benchmark of the measures HV and HF because under the null hypothesis of no herding it could be possible that HF(i) (HV(i) respectively) is positive although there is no herding and the fund managers decide independently. Therefore, we have to define a benchmark that measures the value of HF (HV):

$$\frac{|\chi'_b - \chi'_s|}{\chi'_b + \chi'_s} \qquad (4)$$

where χ'_b (χ'_s) is the probability that a volume x is a net buying (χ'_b) or a net selling (χ'_s) volume. If we assume that the buy and sell actions of funds respectively follow a binomial distribution with value 1 if the fund is a net buyer and a net seller respectively and zero otherwise it is possible to calculate the probability that a volume x is a net buying or a net selling volume if the traded volume of active funds in a period is n (analogously for the number of managers, HF). For example, the benchmark for the first half of 1993 amounts to 0.022 for HV. The benchmarks for the other periods (and for HF) are quite similar. In sum, under the null hypothesis of no herding both ratios are virtually zero.

All analyses were conducted with two groups of mutual funds because of differing reporting dates (see above). The results for the mutual funds with calendar-year reporting (June, December) show strong similarity to the ratios of the second group (March, September). Consequently, the following section documents the findings from the first group only.

Table 1 (2) presents the results of the ratio HV (HF) across all stocks in a given half-year period. The mean value of HV is about 0.8 for each period (table 1). The average of HF is slightly lower (table 2) and shows a greater spread. MAD–μ, MAD–ME, and R are also measures for dispersion. The values of about 0.24 (MAD–μ, HV), 0.18 (MAD–ME, HV), 0.34 (MAD–μ, HF), 0.28 (MAD–ME, HF) show again the difference be-

Table 1: Descriptive statistics for the HV ratio in each half-year period

Coefficient	half-year period (from...to) HV										
	0188 0688	0788 1288	0189 0689	0789 1289	0190 0690	0790 1290	0191 0691	0791 1291	0192 0692	0792 1292	0193 0693
m	0.83	0.83	0.78	0.78	0.81	0.85	0.82	0.82	0.81	0.82	0.83
s	0.31	0.25	0.30	0.32	0.28	0.27	0.29	0.30	0.29	0.30	0.29
VC	0.37	0.30	0.38	0.41	0.35	0.32	0.35	0.36	0.36	0.36	0.35
MAD–m	0.25	0.21	0.26	0.28	0.24	0.21	0.23	0.24	0.24	0.24	0.24
R	0.99	0.87	0.97	1.00	0,94	1.00	1.00	1.00	1.00	1.00	0.97
ME	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MAD–ME	0.17	0.17	0.22	0.22	0.20	0.15	0.18	0.18	0.19	0.18	0.17

Notes: μ = mean value; s = standard deviation; VC = s / μ; MAD–μ = mean absolute deviation of mean; R = range; ME = Median; MAD–ME = mean absolute deviation of median

Table 2: Descriptive statistics for the HF ratio in each half-year period

Coefficient	half-year period (from...to) HF										
	0188	0788	0189	0789	0190	0790	0191	0791	0192	0792	0193
	0688	1288	0689	1289	0690	1290	0691	1291	0692	1292	0693
m	0.80	0.67	0.70	0.68	0.70	0.78	0.73	0.73	0.70	0.69	0.76
s	0.33	0.40	0.37	0.40	0.39	0.36	0.39	0.38	0.39	0.40	0.35
VC	0.41	0.60	0.53	0.59	0.56	0.46	0.53	0.52	0.56	0.58	0.46
MAD–m	0.28	0.38	0.33	0.37	0.36	0.31	0.35	0.34	0.35	0.37	0.31
R	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ME	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MAD–ME	0.20	0.33	0.30	0.31	0.29	0.23	0.27	0.27	0.30	0.31	0.27

Notes: μ = mean value; s = standard deviation; VC = s / μ; MAD–μ = mean absolute deviation of mean; R = range; ME = Median; MAD–ME = mean absolute deviation of median

tween HV and HF as stated above. R is 1 in almost every period.

Thus, the data in both tables reveal strong tendency of benchmark herding in every period. Therefore, *Hypothesis 2* cannot be rejected.

Because of the fact that HV is the more convincing ratio the following results are reported only with this measure.

The results up to now were derived under the assumption that each money manager is only responsible for one mutual fund, ignoring the possibility that an investment company may own more than one fund. A reversal of this assumption requires net changes in holdings to be summed for each investment company (including all mutual funds owned) (cf. GTW 1996 for a study which only calculates ratios corresponding to funds and not to managers and single stocks).

Our findings under the reversed conditions (fund companies, not fund managers) are consistent with our assumption that each fund manager is responsible for one mutual fund on average. The value of HV (regarding investment companies) is slightly higher (about 5%) than the equivalent value from the analysis of fund managers (see table 1). This means a small compensation of buy and sell activities within the investment companies (remember the calculation of the measure).

The following section presents results from the HV ratio for different groups of stocks.

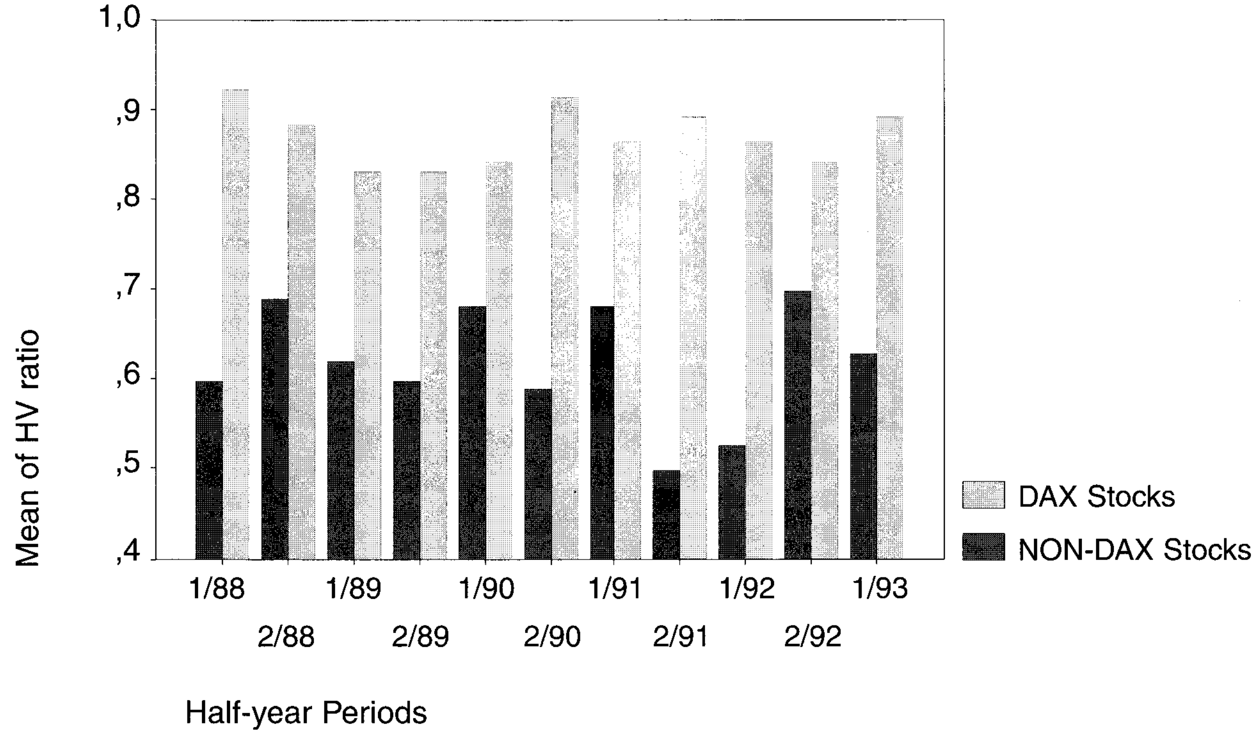
4.3 Further results – groups of stocks

Results for stocks represented in the DAX compared with others

The stocks included in the DAX (German stock index) are 30 leaders of the official market segment which were selected due to their high turnovers, large market capitalization, and early opening quotations. These stocks gather about 60 percent of listed German companies' book equity, amounting to more than 30% of turnovers, and to more than three quarters of the free float.

Figure 2 documents the results for HV divided into the two groups of stocks, DAX stocks and Non-DAX stocks. The lower left bars represent the ratios for the DAX stocks. The value of HV of the other stocks is about 50% higher. So, herding seems to be stronger in smaller and partially less liquid stocks that are not included in the stock

Figure 2: Mean value of HV for single stocks categorized on DAX vs. Non-DAX stocks in each half-year period



index. But in both groups a strong tendency of herding among the money managers is revealed.

A possible explanation for the difference in herding between the two groups of stocks addresses the information acquisition models cited above (section 2.1). If one assumes that there is less information available (concerning quantity and quality) about Non-DAX companies, fund managers may be more likely to follow the trading of their competitors. This corresponds to the cascade model of WELCH and of BANERJEE, too, which postulates a rational inference based on very limited information. Money managers´ behavior can be enforced by the smaller market depth (liquidity) of Non-DAX stocks. The results are also consistent with the theoretical concept of SCHARFSTEIN/STEIN that explains herding behavior by agency problems. Following a benchmark like a market index, on principle, we can assume that the high quantity and quality of information about the blue chips lead to some variation in their interpretation, and herding occurs slightly lower than in the other stocks. The latter group of investment alternatives is more risky for money managers because of its lower market depth, and the potentially poorer quality and quantity of information (only a few analysts are able to interpret the data from the companies). So, if a peer group invests or deinvests in such stocks the other managers follow more quickly and with less variations in their behavior than they do in the index stocks. Therefore, a stronger tendency of herding is observed in Non-DAX stocks in contrast to DAX stocks.

Herding in small caps?

The result from the previous section gives a first hint that our data cannot reject Hypothesis 3. To analyze this more deeply and to compare it to the LSV paper we now focus on the firm size and

Table 3: Descriptive statistics for the HV ratio for stocks categorized on firm size (measured on market capitalization) for a typical period (first half of 1993)

Coefficient	Firm size in million of DM (market capitalization), HV					
	<100	<500	<2500	<5000	<10000	<=10000
m	0.97	0.87	0.90	0.89	0.65	0.47
s	0.08	0.27	0.24	0.27	0.33	0.24
VC	0.08	0.31	0.27	0.30	0.51	0.51
MAD–m	0.05	0.21	0.16	0.17	0.31	0.20
R	0.24	0.94	0.92	0.97	0.86	0.77
ME	1.00	1.00	1.00	1.00	0.66	0.51
MAD–ME	0.03	0.13	0.10	0.11	0.35	0.54

Notes: μ = mean value; s = standard deviation; VC = s / μ; MAD–μ = mean absolute deviation of mean; R = range; ME = Median; MAD–ME = mean absolute deviation of median

address whether there is (stronger) herding in small stocks (stocks with small market capitalization). The stocks in which the fund managers were active in a given period are divided into size categories. We use both book equity and market capitalization as criteria (the categories used in our study are shown in the head of table 3). Both procedures reach similar findings. Therefore, this paper only presents data calculated on the basis of market capitalization (table 3). The documentation is limited to the first half of 1993 because the results from the other periods do not differ fundamentally.

The findings in table 3 reveal significant differences in herding between some of the six categories. The smallest stocks (column 1, HV: 0.97) are substantially more afflicted by herding behavior than the largest and the second largest stocks (column 5 and 6, HV: 0.65 and 0.47, respectively).[5] Our results support the findings of the LSV study. *Hypothesis 3* cannot be rejected. The data provide also an empirical hint to the results of ZEGHAL (1994) who has found a positive correlation between the availability of information and firm size.

The market capitalization of a stock can also be interpreted as a proxy for the liquidity of a stock (market depth). To control for the liquidity factor as a determinant of more or less herding in small stocks, we apply a second proxy for market depth, the free float of a listed company. In our analysis free float is defined as the proportion of shares circulating in the market, i.e. shares available for all market participants. The higher the free float, the deeper is the market in a given stock.

The results only show weak evidence for stronger herding in stocks with low free float. Thus, we suggest that market depth is a less influencing variable of herding in small caps´ stocks than information acquisition and cascade effects.[6]

Results regarding industries

In addition to the considerations in the literature, we analyze whether herding differs between the industries. Therefore, we differentiate 12 industry sectors. The selected industries and the mean value of HV across all half-year periods in each group of stocks are presented in table 4. The data reveal significant differences in herding behavior.[7] Industries like Data systems, Consumption goods or Traffic show a stronger tendency of herding than sectors like Life insurance, Automo-

Table 4: Mean value of HV for single stocks categorized on industries across all periods

Selected industries	HV (across all periods)
Glass	1.00
Data systems tech.	0.99
Breweries/beverage	0.97
Consumption goods	0.97
Traffic/transport	0.95
Mortgage banks	0.93
Property insurance comp.	0.91
Average	0.82
Commercial banks	0.72
Food	0.72
Chemicals	0.71
Automobile	0.65
Life insurance comp.	0.64

bile or Chemicals. While economical significance is clear cut, we use a MANN-WHITNEY´s U-test to test for statistical significance (see footnote above, section 4.3.2). The data from the test are presented in table A in the Appendix. It quotes the probability of rejecting the null hypothesis: The hypothesis that a sample of the industries above the average and a sample of the industries below it are from the same population can be rejected – with two exceptions (Food vs. Traffic and Food vs. Property insurance) – on a 95% confidence level. Within the seven industries revealing the strongest herding behavior the tests could not expose significant differences. The same holds true for the last five industries except the Food sector (which does not fit in this pattern at all).
The results can be explained by two different factors, the firm size (calculated on market capitalization) categories and the free float. Companies belonging to industries with a strong tendency of herding (e.g., Glass or Data systems with a mean small firm size and low free float. Thus, the arguments in the two sections above can be applied.

5. Summary and conclusions

Our study of end-of-half-year portfolio holdings of 28 German open-end domestic stocks mutual funds which represent almost the whole industry in the period from 1988 to 1993 finds a strong tendency of benchmark or market-wide herding. Consistent to the results of the LSV study we reveal no excess or stock-picking herding at all.
In deeper analyses the results show a significant stronger tendency of benchmark herding for small stocks and for selected industries. The latter finding is probably caused by firm size.
Overall, we can state that investment decisions of money managers tend to end up less on the same side of the market in stocks included in the stock index (DAX). Also small caps are more afflicted by herding then other stocks. These results support the predictions of the theoretical literature like the information acquisition model, the relative performance compensation model, or the cascade model. Additionally, the data reveal significant differences in herding behavior between the stocks of different industries.
To improve the results from our medium-term analysis (half year) in order to draw more general conclusions future research has to address more (high) frequent data. Under such conditions it is possible to control for market-timing strategies and price-destabilizing effects of institutionals. This would enable us to support or reject well-known appraisals of the kind „If a fund is engaged in a (less liquid) stock then the price movement is significant".[8]

Appendix

Table A: MANN-WHITNEY´s U-test corresponding to Table 4

Industry	1	2	3	4	5	6	7		8	9	10	11	12
1	–	1.000	0.558	1.000	0.078	1.000	0.144		0.000	0.024	0.000	0.000	0.000
2	1.000		0.682	0.333	0.156	1.000	0.198		0.000	0.039	0.000	0.000	0.000
3	0.558	0.682		0.251	0.146	1.000	0.398		0.000	0.011	0.000	0.000	0.000
4	1.000	0.333	0.251		0.006	0.367	0.026		0.000	0.000	0.000	0.000	0.000
5	0.078	0.156	0.146	0.006		0.211	0.750		0.000	0.293	0.000	0.000	0.002
6	1.000	1.000	1.000	0.367	0.211		0.327		0.000	0.040	0.000	0.000	0.000
7	0.144	0.198	0.398	0.026	0.750	0.327			0.000	0.208	0.000	0.000	0.001
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000			0.006	0.677	0.581	0.936
9	0.024	0.039	0.011	0.000	0.293	0.040	0.208		0.006		0.003	0.005	0.028
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.677	0.003		0.867	0.662
11	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.581	0.005	0.867		0.662
12	0.000	0.000	0.000	0.000	0.002	0.000	0.001		0.936	0.028	0.662	0.662	

Notes: 1 – Glass; 2 – Data systems; 3 – Breweries; 4 – Consumption; 5 – Traffic; 6 – Mortgage banks; 7 – Property insurance; 8 – Commercial banks; 9 – Food; 10 – Chemicals; 11 – Automobile; 12 – Life insurance.

Footnotes

[1] SCHARFSTEIN and STEIN (p. 465) give the hint to look at KEYNES´ s General Theory for basic work: „Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally“ (KEYNES 1936, 158).

[2] LSV (p. 30): „Each quarterly p is the number of money managers buying relative to the number active, aggregated across all stocks that the money managers traded in that year.“

[3] Finally, in the first part of the LSV paper the authors only look at the number of the money managers and they do not calculate the volume of shares (or $). But the latter is the more interesting variable if one wants to estimate institutionals´ price impact.

[4] Because of the compulsory disclosure regulations only this data were available. Except of one fund all money managers were not willing or able to provide us with monthly, weekly or daily data voluntarily on request.

[5] While economic significance is clear cut, we use a MANN-WHITNEY´s U-test to compare the results between column 1 and columns 5 and 6 of table 3 for statistical significance. The test investigates location differences (shift in distribution) between unrelated samples from the same distribution. It is a non-parametric test analogous to the t-test for the mean. It tests the null hypothesis that the samples can be thought of as a single sample from one population. It compares the number of times a score from sample X shows a higher rank than a score from sample Y. The z-stat for the comparison of the lowest and the second highest (highest) class is 0.0145 (0.0001). More test data are available from the author.

[6] In addition, we control for other determinants like the number of active managers and the volume traded. We find that the distribution of the number of active managers and the trading volume shows no systematic pattern between the size categories.

[7] While economical significance is clear cut, we use a MANN-WHITNEY´s U-test to test for statistical significance (see footnote above). The data from the test are presented in table A in the Appendix. The table A quotes the probability of rejecting the null hypothesis.

[8] Cf. MÜHLBRADT/DIRMEIER 1997, 403 (translated by the author), for example.

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