Measuring mutual fund herding – A structural approach

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❖ Objectives and motivations of the study :

This paper proposes a methodological improvement to empirical studies of herd behavio based on investor transactions. Herd behavior suggests that there are limits to human beings' free will. The actions of a large group can greatly influence an individual's decisions.

In this article, they show that the traditionally used herding measure produces biased results. This bias depends on characteristics of the data and also affects the robustness of previous findings. Which is why they derive a new measure that is unbiased and shows superior statistical properties for data sets commonly used.

❖ Used data :

- Standard measure of herding developed in Lakonishok et al. (1992).
- Hand collected database introduced by Walter and Weber (2006) that has been extended to cover the period from 1998 to 2004. Our data contains portfolio holdings of mutual funds specializing in German stocks.

Indicators / Méthods / Models used :

#0 : Traditional herding statistics model (Lakonishok et al.)(1992) :

Consider an individual stock-quarter qs and a total of S stocks traded in quarter q. The traditional herding statistic for s in q is given by

$$H_{|1|}^{qs} = \left| \frac{b^{qs}}{n^{qs}} - \hat{\pi}^q \right| - \underbrace{E\left[\left| \frac{\tilde{b}^{qs}}{n^{qs}} - \hat{\pi}^q \right| ; \tilde{b}^{qs} \sim B(\hat{\pi}^q, n^{qs}) \right]}_{AF^{qs}} \tag{3}$$

where b^{qs} is the number of buy transactions and n^{qs} the total number of transactions in stock s during quarter q.[7] The parameter $\hat{\pi}^q = \frac{\sum_{s=1}^{S} b^{qs}}{\sum_{s=1}^{S} n^{qs}}$ gives the average proportion of buys to total transactions in all S stocks in the quarter and thus the expected probability of a buy under the null hypothesis of no herding. The left-hand term in the $H_{|1|}^{qs}$ expression will be positive even under the null hypothesis: some degree of dispersion is to be expected given a finite number of stochastic transactions (normal dispersion). The second term, the adjustment factor AF^{qs}, corrects for this expected dispersion. $E[.; \tilde{b}^{qs} \sim B(\hat{\pi}^q, n^{qs})]$ thus is the expected value of the expression in square brackets when the number of buys $\tilde{b}^{qs}$ is distributed binomially with probability $\hat{\pi}^q$ and n^{qs} independent draws. Overall, a positive herding statistic thus captures excessive dispersion on the buy or sell side at stock-quarter level.

Two components on this model :

- The expected absolute dispersion when there is herding in stock s (denoted EADH)
- The adjustment factor (AF) as functions of the number of trades in the stock.

Without AF, the herding statistic would oberstate the true level of herding since some degree of dispersion always results from the stochastic nature of trading behavior. However, AF can also overcorrects and lead to an understatement of herding.

We can notice that the bias becomes negligible only for very high numbers of trades in a stock.

Model created for the study :

With this information at hand, we construct the following simple model: Consider stock s during quarter q (henceforth called stock-quarter qs). Let the probability that this stock is bought (versus sold) by a fund manager active in qs be

$$\pi^{qs} = \pi^{q} + \iota^{qs}\delta^{qs} \tag{1}$$

where

$$\iota^{qs} = \begin{cases} 1 & \text{with Prob} = 0.5 \\ -1 & \text{with Prob} = 0.5 \end{cases} \tag{2}$$

In (1), π^{q} denotes the overall probability of buys in quarter q for all stocks (determined by new money flows, for example), δ^{qs} is the degree of herding in stock-quarter qs and ι^{qs} is an unobservable (latent) variable indicating whether herding in the stock-quarter is on the buy ($\iota^{qs} = 1$) or sell side ($\iota^{qs} = -1$).

with well-documented statistical properties.[10] As before we estimate in a first step the probability of buys in a quarter by $\hat{\pi}^{q}$. Our suggested measure of herding in stock s during quarter q is

$$\mathbb{H}_2^{qs} = \frac{(b^{qs} - \hat{\pi}^{q} n^{qs})^2 - n^{qs}\hat{\pi}^{q}(1-\hat{\pi}^{q})}{n^{qs}(n^{qs}-1)} \quad , \tag{4}$$

where the numerator is the empirical variance minus the expected variance of a binomial distribution with parameters n^{qs} and $\hat{\pi}^{q}$. This formula is the complement to the traditional measure (now for the second moment), except for the normalization in the denominator which leads to more desirable statistical properties.[11]

The $\mathbb{H}_2$ measure may be aggregated over stock-periods: Let the set of aggregated stock-periods be labeled $\mathcal{A}$. The aggregate's measure of herding is then given by

$$\mathbb{H}_2^{\mathcal{A}} = \frac{1}{\#\mathcal{A}} \sum_{qs \in \mathcal{A}} \mathbb{H}_2^{qs}. \tag{5}$$

Finally, in order to make the level of the new herding measure comparable to the traditional measure we use the square root of the aggregated herding measure

$$H_2^{\mathcal{A}} \equiv \sqrt{\mathbb{H}_2^{\mathcal{A}}}. \tag{6}$$

In contrast to the $H_{|1|}$ measure, we can derive the following statistical properties of the $\mathbb{H}_2$ measure (and its variants) in closed form.

1 $\mathbb{H}_2^{qs}$ is an unbiased estimator of $(\delta^{qs})^2$.
2 $\mathbb{H}_2^{\mathcal{A}}$ is an unbiased estimator of $(\delta^{\mathcal{A}})^2$, as defined above.
3 $H_2^{\mathcal{A}}$ is a consistent estimator of $\delta^{\mathcal{A}}$ (that is, for $\#\mathcal{A}$ approaching infinity).

The formal derivation of these as well as further statistical properties of the alternative measure is provided in a web-appendix.

#1 : Comparing the two measures : In this study, they have argued that the traditional herding measure H1 and the new H2 measure (the square root of H2) differ in terms of accurateness in estimating δ. However it's not clear witch of the two measures performs statistically better in our model.

#2 : Empirical analysis : They analyse the herding behavior of institutional investors in the German stock market using their new measure of herding. We can see different measures.

- Herding and trading intensity
- Hearding and stock size
- Hearding in su-periods

❖ Results :

#0 : Results show that for the number of trades found in typical empirical studies, the size of the bias is non négligeable. Patterns of herding found among subsets of the data might be affected solely by the functional form of the bias.

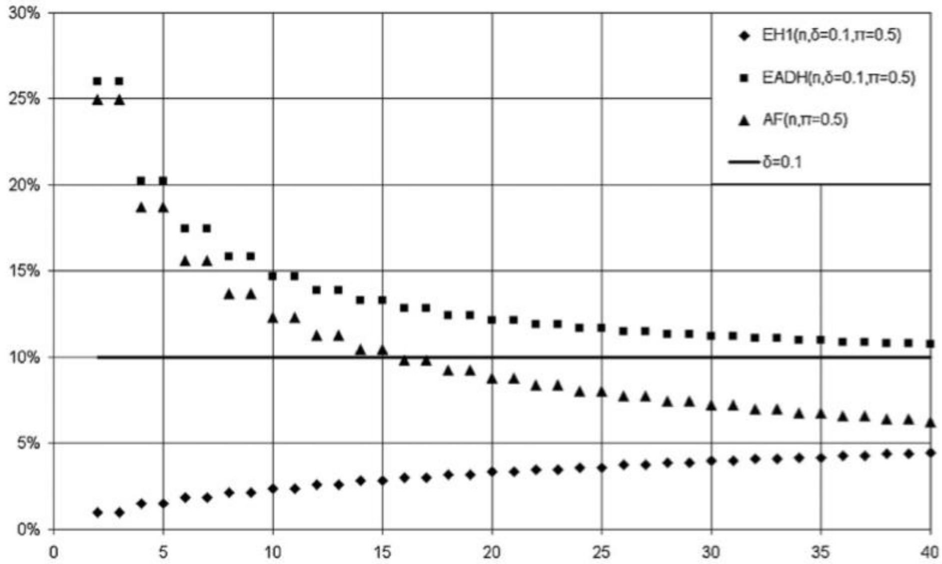

Fig. 1. Expected $H^{qs}_{|1|}$ statistic and components. *Notes*: The figure shows (in percentages) a stock's expected $H_{|1|}$ measure (EH1) and its two components, the expected absolute dispersion (EADH) and the adjustment factor (AF) as functions of the number of trades in the stock. It also shows the true underlying herding parameter of 10%. See Appendix A for information on calculations and parameter inputs.

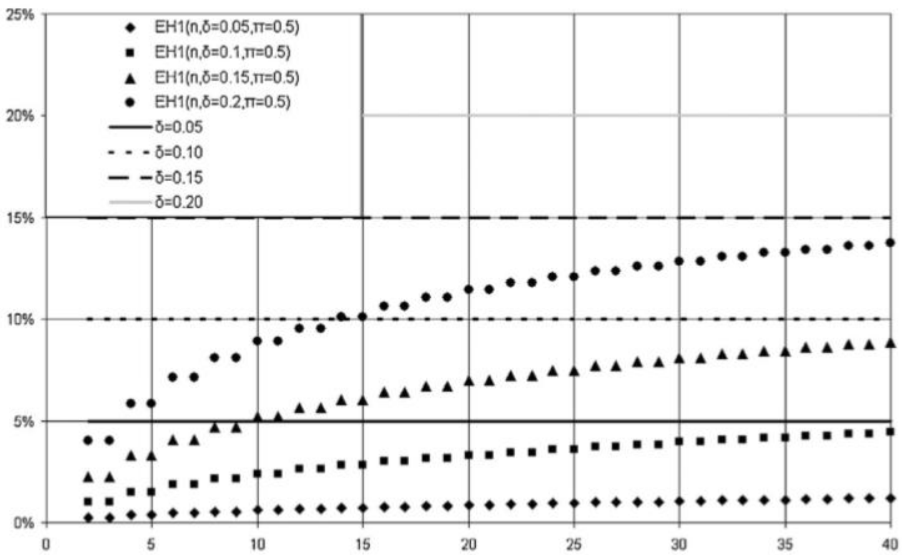

Fig. 2. Expected $H^{qs}_{|1|}$ statistics and true herding parameters. *Notes*: The figure shows (in percentages) the expected $H_{|1|}$ measure (EH1) for various levels of true herding (δ) as functions of the number of trades in the stocks, as well as the levels themselves. See Appendix A for information on calculations and parameter inputs.

#1 : We identify two basic applications for any herding measure :

- To test whether there is herding in the sample under investigation
- To measure the extent of herding (if it exists)

The H1 measure is very well suited for the first task. Table 4 shows that both H1 and H2 are valid tests. Figure 4 suggests a small advantage of H1 in small samples compared to H2.

#2 :

Herding and trading intensity :

Table 6
Herding and trading intensity (sub-samples).

FM trading	$H_{\|1\|}$	H_2	$\frac{H_2 - H_{\|1\|}}{H_2}$	Number of stock-periods	Average number of trades
$3 \leq n \leq 4$	0.0375 (0.0064)	0.1720 (0.0165)	78%	620	3.4
$5 \leq n \leq 9$	0.0476 (0.0068)	0.1733 (0.0125)	73%	455	6.4
$10 \leq n \leq 14$	0.0393 (0.0081)	0.1364 (0.0144)	71%	203	12.2
$15 \leq n \leq 19$	0.0438 (0.0064)	0.1363 (0.0111)	68%	299	17.2
$20 \leq n \leq 24$	0.0544 (0.0067)	0.1426 (0.0105)	62%	249	21.7
$n \geq 25$	0.0788 (0.0190)	0.1734 (0.0224)	55%	39	25.7

Notes: This table reports herding measures $H_{|1|}$ and H_2 for Germany for various minimum thresholds for the number of transactions per stock. Corresponding standard errors are given in parentheses below the estimates. The relative bias, number of stock-periods and average number of trades per stock in each class are also reported.

Their new measure is 2.8 times higher than the traditional measure of herding (on average). The relative bias between H2 and H1 measure decreases as expected with higher trading activity.

Herding and stock size :

Table 7
Herding and stock size.

Market cap quintile	$H_{\|1\|}$	H_2	$\frac{H_2 - H_{\|1\|}}{H_2}$	Number of stock-periods	Average number of trades
1 (largest stocks)	0.0691 (0.0112)	0.1625 (0.0158)	57%	108	19.7
2	0.0468 (0.0093)	0.1371 (0.0157)	66%	137	20.0
3	0.0319 (0.0081)	0.1239 (0.0188)	74%	220	16.3
4	0.0453 (0.0059)	0.1565 (0.0132)	71%	492	10.6
5 (smallest stocks)	0.0434 (0.0050)	0.1715 (0.0113)	75%	908	5.9

Notes: This table reports herding measures $H_{|1|}$ and H_2 for Germany for sub-samples of stocks according to market capitalization. Total market capitalization of all stocks is split into quintiles, with stocks in quintile 1 having the largest market cap and stocks in quintile 5 having the smallest market cap. The reference year for classification was 2005. Corresponding standard errors are given in parentheses below the estimates. The relative bias, number of stock-periods and average number of trades per stock in each sub-sample are also reported.

Higher herding among small stocks might be attributed to less information abailable and hence ro managers being more inclined to follow others theres companies are closesly followed by a large number of analyst and money managers, all relying on the same information.

They expect here higher levels of herding measured by H1 for larger stocks due to the lower bias. The effect is confirmed in their data.

Herding in sub-periods :

Unlike in the table before, there is no clear-cut trend between the average number of trades and the number of stock periods.

Table 8
Herding in sub-periods.

Year	$H_{\|1\|}$	H_2	$\frac{H_2-H_{\|1\|}}{H_2}$	Number of stock-periods	Average number of trades
1998	0.0474 (0.0112)	0.1690 (0.0240)	72%	164	9.4
1999	0.0379 (0.0088)	0.1534 (0.0215)	75%	233	10.2
2000	0.0563 (0.0084)	0.1875 (0.0170)	70%	275	9.7
2001	0.0740 (0.0087)	0.2026 (0.0160)	63%	271	10.8
2002	0.0215 (0.0075)	0.0871 (0.0289)	75%	273	11.0
2003	0.0475 (0.0079)	0.1681 (0.0161)	72%	291	11.0
2004	0.0301 (0.0071)	0.1328 (0.0197)	77%	358	9.3

Notes: This table reports herding measures $H_{|1|}$ and H_2 for Germany for sub-periods (years). Corresponding standard errors are given in parentheses below the estimates. The relative bias, number of stock-periods and average number of trades per stock in each sub-sample are also reported.

❖ Conclusion :

This paper argues that when measuring the degree of herding (either in terms of absolute levels, in mean comparisons among samples or in regression analyses), relying on the traditional herding statistic introduces in Lakonishok (1992) may produces results that are difficult to interpret.
While a general distortion in the traditional measure might not matter a lot, this study show that the bias interacts with other parameters in data set and might mislead researchers in their conclusions. This new unbiased measure provides new insights into fund manager herding that would have been undetected under the traditional statistic.