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Short-term Herding of Institutional Traders: New Evidence from the German Stock Market

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Abstract

This paper employs a new and comprehensive data set to investigate short-term herding behaviour of institutional investors. Using data of all transactions made by financial institutions in the German stock market, we show that herding behaviour occurs on a daily basis. However, in contrast to longer-term herding measures obtained from quarterly data, results based on daily data do not indicate that short-term herding tends to be more pronounced in small capitalised stocks or in times of market stress. Moreover, we find that herding measures based on anonymous transactions can lead to misleading results about the behaviour of institutional investors during the recent financial crisis.

Keywords: *herding*, *investor behaviour*, *institutional trading*, *anonymous transaction data*

JEL classification: *D*81, *G*11, *G*24

1. Introduction

Herding behaviour of investors, defined as the tendency to accumulate on the same side of the market, is often viewed as a significant threat for the stability and the efficiency of financial markets, see Hirshleifer and Teoh (2003) and Hwang and Salmon (2004). The empirical literature on herding behaviour in financial markets is particularly interested in the investment behaviour of institutional investors, i.e., of banks and other financial institutions, see e.g. Barber *et al.* (2009). Yet, the evidence on herding behaviour of institutional investors is mixed and partly elusive.

The evidence on herding is often impeded by data availability problems. In particular, positions taken by institutions on the stock market are reported only infrequently, if at all.

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For example, for US mutual funds reports of holdings are available only on a quarterly basis, see e.g. Choi and Sias (2009). Evidence for German mutual funds even had to be based on semi-annual data, see Walter and Weber (2006). In highly-developed financial markets, however, herding might also occur within shorter time intervals.

Several contributions, including Barber *et al.* (2009), attempt to overcome the problem of data frequency by using anonymous transaction data instead of reported holdings. Since those data do not identify the trader, researchers usually separate trades by size and then simply define trades above a specific cutoff size as institutional. However, even though large trades are almost exclusively the province of institutions, institutions with superior information might split their trades to hide their informational advantage. While low-frequency data may still contain useful information about longer-term herding, the interpretation of herding measures based on anonymous transactions is not without problems. In particular, it is not clear whether the strategic trading behaviour of institutional investors tends to increase or decrease the evidence on herding.

The current paper sheds more light on the empirical relevance of short-term herding by introducing a new and comprehensive data-set on German stock market transactions that includes both high-frequency and investor-level data. Our analysis provides new evidence on the herding behaviour of financial institutions for a broad cross-section of stocks over the period from July 2006 to March 2009 in the German stock market. In order to investigate how the underlying data frequency may affect the empirical assessment of short-term herding, we evaluate herding measures at daily, monthly, and quarterly frequency. Neglecting the investor-related information contained in our data set, we explore how herding measures are affected by the use of anonymous transaction data.

The empirical results suggest that previous studies based on low-frequent or anonymous transaction data might have overestimated the extent of short-term herding. This conclusion holds irrespective of the herding measure applied. Confirming the results obtained with the static herding measure proposed by Lakonishok *et al.* (1992), the dynamic measure of Sias (2004) shows that institutional trades are correlated over time. However, although there are investors who follow other traders, the main part of the correlation results from institutions that follow their *own* trading strategy. We find that daily herding measures typically contradict implications of herding theory. In particular, it is not confirmed that short-term herding is more pronounced in smaller and less liquid stocks. Moreover, our results do not indicate that short-term herding increases in times of market stress, i.e., during the recent financial crisis. It is worth noting, however, that conclusions concerning the impact of the financial crisis on the trading behaviour of institutional investors would have been misleading if herding measures were based on anonymous transaction data.

The rest of the paper is structured as follows: Section 2 briefly reviews the literature on herding. Section 3 discusses the role of data availability on the herding measure. Section 4 introduces the applied herding measures. Section 5 presents the empirical results and Section 6 offers some conclusions.

2. Herding: A Brief Review of the Literature

2.1. *Types of herding*

Following e.g. Bikhchandani and Sharma (2001), herding describes the tendency of institutions or individuals to show similarity in their behaviour and thus act like a herd.

Recent economic theory distinguishes between intentional herding and unintentional, or spurious herding.[1] *Unintentional herding* is mainly fundamental driven and arises because institutions may examine the same factors and receive correlated private information, leading them to arrive at similar conclusions regarding individual stocks, see e.g., Hirshleifer *et al.* (1994). Moreover, professionals may constitute a relatively homogenous group: they share a similar educational background and professional qualifications and tend to interpret informational signals similarly.

In contrast, *intentional herding* is more sentiment-driven and involves the imitation of other market participants, resulting in simultaneous buying or selling of the same stocks regardless of prior beliefs or information sets. This type of herding can lead to asset prices failing to reflect fundamental information, exacerbation of volatility, and destabilisation of markets, thus having the potential to create, or at least contribute, to bubbles and crashes on financial markets, see e.g. Morris and Shin (1999) and Persaud (2000). Yet, several economic theories including models of information cascades (Avery and Zemsky, 1998) and reputation (Scharfstein and Stein, 1990) show that even intentional herding can be rational from the trader's perspective.

Models of intentional herding typically assume that there is only little reliable information in the market and that traders are uncertain about their decisions and thus follow the crowd. In contrast, in the case of unintentional herding, traders acknowledge public information as reliable, interpret it similarly and thus they all end up on the same side of the market. For both types of herding, the degree of herding is linked to the uncertainty or availability of information.

2.2. *Determinants of herding*

2.2.1. *Size effects and the development of the market.* The empirical literature explores the determinants of herding via the link between herding and information availability. Lakonishok *et al.* (1992) segregate stocks by size because market capitalisation of firms usually reflects the quantity and quality of information available. Thus, one would expect higher levels of herding in trading small stocks as evidence of intentional herding. In line with theoretical predictions, they find evidence of herding being more intense among small companies compared to large stocks. Further empirical evidence on the link between herding and size is provided by Wermers (1999) and Sias (2004).[2]

Based on semi-annual data, Walter and Weber (2006) and Oehler and Wendt (2009) report significant positive and higher levels of herding for German mutual funds compared to those found in US-based research. Walter and Weber (2006) link the finding of herding to the stage of development of the financial market. They argue that the German market is not as highly developed as the US and UK capital markets. There is also evidence for higher herding levels in emerging markets compared to developed

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[1] For a comprehensive survey of the theoretical and empirical herding literature, see e.g. Hirshleifer and Teoh (2003).

[2] An alternative, less direct approach to analyse herding behaviour is proposed by Christie and Huang (1995), where herding is measured for the whole market and not for a specific group of market participants. Assuming that herding occurs when individual investors neglect their own information and simply follow the crowd, herding implies that the dispersion of cross-sectional returns decreases in times of higher uncertainty, i.e., when the volatility of returns is large, see Chiang and Zheng (2010).

ones.[3] High herding in emerging markets may be attributed to incomplete regulatory frameworks, especially in the area of market transparency. Deficiencies in corporate disclosure and information quality create uncertainty in the market, throw doubt on the reliability of public information, and thus impede fundamental analysis, see Antoniou *et al.* (1997) and Gelos and Wei (2002). Kallinterakis and Kratunova (2007) argue that in such an environment it is reasonable to assume that investors will prefer to base their trading on their peers' observed actions. Thus, intentional herding through information cascades is more likely to occur in less developed markets. In the current paper, we assume that the degree of market transparency increases with the size of the traded stocks. As a result, less herding in larger stocks may also appear because the corresponding markets are more highly developed and, thus, more transparent.

2.2.2. *State of the market*. The extent of herding may depend on the state of the overall market. Choe *et al.* (1999) find higher herding levels before the Asian crisis of 1997 than during the crises for the Korean stock market. Using data from the Jakarta Stock Exchange, Bowe and Domuta (2004) show that herding by foreigners increased following the outbreak of the crisis. Analysing the relationship between the cross-sectional dispersion of returns and their volatility, Chiang and Zheng (2010) conclude that herding behaviour appears to be more apparent during the period in which the financial crisis occurs. In contrast, using data from US and South Korean stock markets, Hwang and Salmon (2004) find higher herding measures during relatively quiet periods than during periods when the market is under stress. In order to account for the state of the market, the following empirical analysis allows for different herding intensities before and during the recent financial crisis.

3. Data

3.1. *Data issues*

3.1.1. *Low frequency*. Most empirical studies on herding in financial markets identify institutional transactions as changes in reported positions in a stock. However, positions are reported very infrequently. For example, the bulk of the literature considers the trading behaviour of US mutual funds who generally report only on a quarterly basis. For German mutual funds, even half-year reports are required.[4] Semi-annual and even quarterly data provide only a crude basis for inferring trades and this frequency might be too low in a rapidly changing stock market environment. Interestingly, the overall effect of the data-frequency on the resulting herding measure is not obvious. On the one hand, herding might be understated, since trades that are completed within the period are not captured. In markets with frequent public information flows and high turnover that lead to the timely incorporation of information, herding behaviour caused by informational

[3] For example, Lobao and Serra (2007) document strong evidence of herding behaviour for Portuguese mutual funds. Significant herding is reported for Indonesia (Bowe and Domuta, 2004), Poland (Voronkova and Bohl, 2005), Korea (Choe *et al.*, 1999; Kim and Wei, 2002) and South Africa (Gilmour and Smit, 2002).

[4] There are also studies that rely on yearly ownership data, see, e.g., Kim and Nofsinger (2005) who investigate herding of financial institutions in Japan. Puckett and Yan (2008) used weekly data to overcome the low frequency problem.

cascades is likely to occur only in the short-term, that is, before public information becomes available. On the other hand, however, herding might also be overstated when looking at a long time interval, since buys at the beginning of the period that are not completed within the period and buys of others at the end are regarded as herding. In order to explore the impact of data frequency on the herding measure, we calculated herding measures based on daily, monthly and quarterly data.

3.1.2. *Identification of traders.* In view of these problems, the recent empirical literature, including Barber *et al.* (2009), attempts to overcome the lack of high-frequency data by using anonymous transaction data.[5] In these contributions, institutional trades are identified by use of a cutoff approach. Transactions above a specific cutoff size are considered as a proxy for institutional trades, since large trades are typically the province of institutions. For example, Lee and Radhakrishna (2000) suggest a cutoff of $50,000 for larger stocks. However, this approach can be misleading if institutions split their trades to hide a superior information advantage. In this case, the most informative institutional trades are probably not the largest ones. Our data confirms that although institutions trade often during a day, those trades are not necessarily large. Herding measures based on anonymous transactions may tend to over- or to understate the true extent of herding. In order to shed more light on the total effect of anonymous transaction data on the herding measure, we ignore the information about the investor contained in our data and calculate the herding measures for various cut-off levels.

3.2. *The BaFin datasource*

Our dataset includes all real-time transactions carried out on German stock exchanges. The data are provided by the German Federal Financial Supervisory Authority (BaFin). Under Section 9 of the German Securities Trading Act, all credit institutions and financial services institutions are required to report to BaFin any transaction in securities or derivatives which are admitted to trading on an organised market.

These records enable the identification of all relevant trade characteristics, including the trader (the institution), the particular stock, time, number of traded shares, price, and the volume of the transaction. Moreover, the records identify on whose behalf the trade was executed, i.e., whether the institution traded for its own account or on behalf of a client that is not a financial institution. Since the aim of our study is the investigation of institutional trades, particularly those of financial institutions, we focus on the trading of own accounts, i.e., those cases when a bank or a financial services institution is clearly the originator of the trade.[6] Using data from July 2006 until March 2009 (a total of 698 trading days), we cover market upturns as well as the recent market downturn.

The analysis focuses on shares listed on the three major German stock indices: the DAX 30 (the index of the 30 largest and most liquid stocks), the MDAX (a mid-cap index of 50 stocks that rank behind the DAX 30 in terms of size and liquidity), and the SDAX

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[5] Because the dynamic Sias herding measure additionally requires the identification of the trader over time, empirical work relying on anonymous transactions employs the static herding measure introduced by Lakonishok *et al.* (1992).

[6] Therefore, we exclude institutions trading exclusively for the purpose of market making. We also exclude institutions that are formally mandated as designated sponsors, i.e., liquidity providers, for a specific stock.

(a small-cap index of 50 stocks that rank behind the MDAX components).[7] Calculating herding measures for these different stock market segments, we explore whether there are differences in the trading behaviour in small and large stocks.

Overall, we have 167,422,502 records of proprietary transactions by 1,120 institutions in those stocks on German stock exchanges. For each institution, we compute the daily trade imbalance. Among these 1,120 traders, 1,044 institutions trade on the DAX 30 stocks, 742 on the MDAX stocks and 512 on the SDAX stocks. On average, about 25 of these institutions trade every day in those stocks, justifying the use of daily data. The institutions have an average daily market share of DAX 30 stocks of about 46%. Interestingly, the market share declined after the start of the financial crises, implying a retraction from trading business. In the period from 1 July 2006 until 8 August 2007, the proportion constituted 66%, shrinking to 32% after August 9, 2007. Table 4 in the Appendix provides further information on the institutions under investigation.

4. Herding Measures

In this section, we briefly review the two herding measures predominantly applied in the literature.

4.1. *The LSV measure*

The first herding measure had been introduced by Lakonishok *et al.* (1992) (LSV measure). According to the LSV measure, herding is defined as the tendency of traders to accumulate on the same side of the market in a specific stock and at the same time, relative to what would be expected if they traded independently.

The LSV herding statistic is given by

$$\boxed{HM_{it} = |br_{it} - \bar{br}_t| - E_t[|br_{it} - \bar{br}_t|]} \tag{1}$$

where br_{it} is the the number of institutions buying stock i at time t as proportion of all institutions trading in i at t. $\bar{br}_t$ is the period average of the buyer ratios over all stocks, which is a proxy for the expected value of the buyer ratio at t, $E_t[br_{it}]$, and thus accounts for an overall signal in the market at time t. Hence, the first term of Equation (1) captures the deviation of the buyers ratio in i at t from the overall buy probability at time t, i.e. captures herding as excess dispersion of what would be expected for that time. The second term, $E_t[|br_{it} - \bar{br}_t|]$, ensures that the herding measure HM_{it} will be zero if the trades are independent.

Following Lakonishok *et al.* (1992), the empirical literature calculates the mean herding measure $\overline{HM}$ as the mean of HM_{it} across all stocks and all periods. A positive and significant value of $\overline{HM}$ indicates the average tendency of the investigated group to accumulate in their trading decisions. The higher the $\overline{HM}$, the stronger the herding. For example, $\overline{HM} = 2\%$ indicates that out of every 100 transaction, two more traders trade on the same side of the market than would be expected if each trader had decided randomly and independently. However, it should be noted that the maximum value of

[7] The stocks were selected according to the index compositions at the end of the observation period on 31 March 2009. The time series of five stocks on the MDAX and five stocks on the SDAX are not complete for the whole period. We have therefore an unbalanced panel of stocks and days, totalling 88,435 observations.

$\overline{HM}$ is not equal to one, even if all traders buy stock i at time t, since HM_{it} is defined as excess or additional herding over the overall trend $\bar{br}_t$. Thus, only stock-picking herding and similar trading patterns beyond market trends are analysed.

4.2. *The Sias measure*

The LSV herding measure is a static measure that detects contemporaneous buying or selling within the same time period. In contrast, the dynamic approach proposed by Sias (2004) explores whether the buying tendency of traders persists over time. The focus of the Sias herding measure is on whether institutional investors follow each others' trades by examining the correlation between institutional trades over time. Similar to the LSV measure, the starting point of the Sias measure is the number of buyers as a fraction of all traders. According to Sias (2004), the ratio is standardised to have zero mean and unit variance:

$$\Delta_{it} = \frac{br_{it} - \bar{br}_t}{\sigma(br_{it})} \tag{2}$$

$\sigma(br_{it})$ is the cross sectional standard deviation of buyer ratios across i stocks at time t. The Sias herding measure is defined as the correlation between the standardised buyer ratios in consecutive periods:

$$\boxed{\Delta_{it} = \beta_t \Delta_{i,t-1} + \epsilon_{it}.} \tag{3}$$

The cross-sectional regression is estimated for each day t and then the time-series average of the coefficients is calculated: $\beta = \frac{\sum_{t=2}^{T} \beta_t}{T-1}$. A high buyer ratio would usually result in a higher LSV measure (if higher than on average) but not necessarily to a higher Sias measure as this depends on the ratio at the next trading day.

The Sias methodology further differentiates between investors who follow the trades of others (i.e., *true herding* according to Sias (2004)) and those who follow their own trades. For this purpose, the correlation is decomposed into two components:

$$\begin{aligned}\beta = \rho(\Delta_{it}, \Delta_{i,t-1}) &= \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \\ &\quad\times \sum_{i=1}^{I}\left[\sum_{n=1}^{N_{it}} \frac{(D_{nit} - \bar{br}_t)(D_{ni,t-1} - \bar{br}_{t-1})}{N_{it}N_{i,t-1}}\right] \\ &\quad+ \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right]\sum_{i=1}^{I}\left[\sum_{n=1}^{N_{it}}\sum_{m=1,m\neq n}^{N_{i,t-1}} \frac{(D_{nit} - \bar{br}_t)(D_{mi,t-1} - \bar{br}_{t-1})}{N_{it}N_{i,t-1}}\right],\end{aligned} \tag{4}$$

where N_{it} is the number of institutions trading stock i at time t and I is the number of stocks traded. D_{nit} is a dummy variable that equals one if institution n is a buyer in i at time t and zero otherwise. $D_{mi,t-1}$ is a dummy variable that equals one if trader m (who is different from trader n) is a buyer at day $t-1$. Therefore, the first part of the measure represents the component of the cross-sectional inter-temporal correlation that results from institutions following their own strategies when buying or selling the same stocks over adjacent days. The second part indicates the portion of correlation resulting from institutions following the trades of others over adjacent days. According to Sias (2004), a positive correlation that results from institutions following other institutions, i.e., the latter part of the decomposed correlation, can be regarded as first evidence for informational cascades.

The analysis on size effects on herding is complicated by large differences in the number of traders. There are typically more institutions trading in large capitalisation stocks than in a small stocks and this will affect both the decomposition of the correlation coefficient and the cross-sectional correlation between the buyers ratios. Therefore, Sias (2004) introduces a modified decomposition of the correlation coefficient β that accounts for the number of traders in a market segment, see Appendix. We will employ these modified measures to assess to what extent correlated trading in different market segments is actually due to traders following the trades of others.

5. Do Institutions Herd?

5.1. *LSV herding*

5.1.1. *Evidence from daily herding measures*. Our results obtained for the static LSV herding are summarised in Table 1. Following the empirical literature, HM_{it} is computed only if at least five traders are active in stock i at time t.[8] Let us first discuss the results obtained for daily investor-level data shown in the first row of each panel. For daily data, the mean value of the herding measure $\overline{HM}$ over the complete sample period and over all stocks is 1.40%. The value is statistically significant but small and slightly lower than found in previous studies using low-frequency data, including Lakonishok *et al.* (1992) and Walter and Weber (2006) who both found herding to be about 2.70%.

Theories on herding behaviour typically predict that herding will be more pronounced in smaller and less liquid stocks, where informational problems should be particularly severe. Our results based on daily data do not confirm this prediction. In contrast, we find that herding for stocks in the DAX30 is 3.65%, i.e., about 2.5 times larger than the herding measure obtained for all stocks. In fact, the daily herding measure for the small stocks defining the SDAX is actually insignificant (t-statistic = −0.57).[9]

If private information gets less reliable in times of market stress, herding measures should be higher during a financial crisis. For each group of stocks, the two lower panels of Table 1 display the average herding measure for the crisis and the non-crisis period,

[8] Table 5 in the Appendix shows that results are robust with respect to different assumptions on minimum numbers of traders. In our application, the resulting loss of observations is not an issue. Table 4 in the Appendix shows that even on the SDAX on average 10.78 institutions are active each day in each stock. Out of the overall panel of stocks and days (88,435 observations), we calculated 87,839 herding measures, i.e., for 542 observations there were no trade imbalances by any institution. Due to the constraint to a minimum of five traders, we lose 3,997 observations for the sample of all institutional traders, i.e., 83,842 observations remain.

[9] In accordance with Lakonishok *et al.* (1992), empirical LSV herding measures below zero should be interpreted as evidence against herding. According to e.g. Bellando (2010), negatively signed LSV herding measures occur because the adjustment factor in Equation (1) can bias the LSV herding measure downwards if the trading intensity is low. This explains why negatively signed herding measures can be observed in case of small stocks. In our application, however, using only observations with a minimum number of 5 traders should ensure that the bias is only small. Notice further that our conclusions hold for different minimum numbers of traders, see Table 5 in the Appendix.

Table 1
LSV herding measures

This table reports mean values of *HM* in percentage terms, calculated at daily frequency, quarterly frequency and with anonymous transaction data (i.e., all transactions below €34,000 for DAX stocks, €14,000 for MDAX stocks and €7,000 for SDAX stocks are dropped) for all stocks and various market segments. Standard errors are given in parentheses.

	All stocks	DAX 30	MDAX	SDAX
Sample period: July 2006 – March 2009				
Daily data	1.40 (0.02)	3.65 (0.04)	1.24 (0.04)	−0.03 (0.05)
Observations	83,842	20,901	33,616	29,325
Quarterly data	2.29 (0.15)	3.59 (0.26)	2.14 (0.23)	1.63 (0.27)
Observations	1,395	331	534	530
Anonymous transactions	4.58 (0.02)	4.39 (0.04)	5.27 (0.04)	3.90 (0.06)
Observations	80,012	20,865	32,438	26,709
Pre-crisis period (<08/09/07)				
Daily data	1.32 (0.04)	4.35 (0.06)	0.99 (0.05)	−0.59 (0.07)
Observations	33,257	8,427	13,005	11,825
Quarterly data	1.63 (0.20)	2.98 (0.41)	1.62 (0.32)	0.82 (0.35)
Observations	523	123	200	200
Anonymous transactions	2.54 (0.03)	2.47 (0.03)	2.54 (0.03)	2.47 (0.07)
Observations	32,751	8,426	12,857	11,468
Crisis period (≥08/09/07)				
Daily data	1.60 (0.03)	3.17 (0.06)	1.41 (0.05)	0.34 (0.07)
Observations	50,585	12,474	20,611	17,500
Quarterly data	2.69 (0.20)	3.95 (0.35)	2.46 (0.31)	2.12 (0.38)
Observations	872	208	334	330
Anonymous transactions	5.99 (0.04)	5.68 (0.05)	5.99 (0.04)	4.97 (0.08)
Observations	47,261	12,439	19,581	15,241

i.e., before and after 9 August 2007 when tensions in the European money market lead to rapid increases in interest rates. For daily data, the evidence found on increased herding during the financial crisis is not very convincing. Short-term herding actually slightly increased in small and medium stocks over the crisis period. For large stocks, however, herding seemed to be more pronounced in the pre-crisis period.

5.1.2. *Effects of data frequency and the use of anonymous transaction data.* The bulk of the literature on herding had to rely either on lower frequency data or anonymous transaction data. In order to investigate the impact these data limitations have on the herding measure, we re-calculate the measures constraining our sample to quarterly data and to trades above a specific size.

Data frequency

In a first step, we calculate herding measures for each institution based on quarterly trade imbalances. In each panel of Table 1, quarterly herding measures are displayed in the second row. With only a few exceptions, herding measures are higher on a quarterly horizon and in a range similar to that found in previous studies using quarterly data. With quarterly data, the degree of herding increases particulary for small-capitalised (SDAX) stocks. Yet, irrespective of the period under consideration and in line with the results obtained for daily data, the results do not suggest that herding is more pronounced in small stocks. Interestingly, in contrast to the daily measures, the quarterly herding measures have significantly increased in the crisis period for all market segments. For brevity, we only present results for quarterly data. Results obtained for monthly data are fully in line with the conclusions on quarterly data and are reported in Table 7 in the Appendix.

Anonymous transaction data

Following the empirical literature using cutoff approaches to identify institutional investors from anonymous transactions, we calculate herding measures for data where all institutional trades below a specific size have been dropped. Lee and Radhakrishna (2000) suggests cutoffs of \$50,000, \$20,000, and \$10,000 for large, medium, and small stocks. Assuming the current level of exchange rates, we adopt that idea and consider only trades in DAX, MDAX, and SDAX stocks that have a volume of more than €34,000, €14,000, and €7,000, respectively. Out of our overall 167,422,502 records we lose 118,307,150 due to this constraint. Ignoring trader identification, we treat every remaining transaction as independent. Consequently, if the same institution trades more than once during a day, its transactions are regarded as trades by different institutions.

For each panel, the resulting herding measures are displayed in the third line of Table 1. With some exceptions during the pre-crisis period, herding measures based on anonymous transactions are significantly higher than those obtained for investor-level data. This suggests that restricting the attention to large trades tends to exaggerate the actual degree of herding. More importantly, however, herding measures based on anonymous transaction data particularly overstate the extent of herding during the crises period. In fact, in contrast to the results obtained for investor-level data, herding measures based on anonymous transactions seemingly indicate that the degree of herding has more than doubled in the crisis period for each market segment. Apparently, the identification of institutional traders through a cut-off approach is particulary difficult in the crisis period. In our application, evidence on herding based on anonymous transaction data leads to misleading conclusions about the role of market stress for the degree of herding.

5.2. *Results on Sias herding*

Table 2 displays the results obtained from the Sias herding measure. The upper part of the table reports the average correlation in percentage terms.[10] The estimated correlation at

[10] Following Sias (2004) and in line with the calculation of the LSV measure, only observations with at least five traders active in i at time t are considered in the estimation. Table 6 in the Appendix display results with different minimum numbers of traders and reveal that results are robust with respect to the assumptions on minimum numbers of traders.

Table 2

Sias herding measures for the *Whole Sample Period*

The upper part of the table reports results for the average correlation in percentage terms of the coefficient β calculated at daily and quarterly frequency and for anonymous transaction data. Below, the table reports the partitioned correlations that result from institutions following their own trades (panel 2) and institutions follow the trades of others (panel 3), see Equation (4). Columns 2–4 of the table show the results from the computation of the cross-sectional average contribution from following their own trades (equation 5) and following others' trades (equation 6) for DAX 30, MDAX and SDAX stocks. Standard errors are given in parentheses.

	All Stocks	DAX 30	MDAX	SDAX
Average correlation				
Daily data	18.01 (0.53)	20.01 (0.68)	18.60 (0.53)	16.84 (0.53)
Observations	83,585	20,715	33,342	29,528
Quarterly data	20.32 (2.77)	20.46 (0.56)	14.06 (3.38)	23.02 (4.57)
Observations	1,260	300	483	477
Anonymous transactions	27.32 (0.35)	22.43 (0.67)	24.96 (0.54)	29.88 (0.60)
Observations	77,295	20,575	31,745	24,975
Follow own trades				
Daily data	10.12 (0.19)	2.02 (0.03)	3.46 (0.04)	5.47 (0.06)
Quarterly data	1.52 (0.70)	0.50 (0.17)	0.26 (0.43)	0.33 (0.56)
Follow trades of others				
Daily data	7.89 (0.23)	0.32 (0.03)	0.26 (0.04)	0.14 (0.06)
Quarterly data	18.80 (1.54)	2.50 (0.17)	2.67 (0.43)	3.13 (0.56)

daily frequency over the complete period and over all stocks is 18.01%, which is slightly higher than the value obtained by Sias (2004) but lower than the result of Puckett and Yan (2008) for weekly frequency. Similar to our results on LSV herding, Sias herding measures obtained from quarterly and anonymous transaction data tend to be higher than those obtained for daily investor-specific data.[11]

Correlated trading can only be attributed to herding behaviour when the correlation in trades has occurred because traders actually followed *other* traders. The lower parts of Table 2 show the results for the partitioned correlation according to the decomposition proposed by Sias (2004), compare Equation 4. Since this decomposition requires the identification of the trader, it cannot be applied to anonymous transaction data. The results shown in the two lower panels of Table 2 reveal that institutions follow their own trades as well as those of others. However, in contrast to the static LSV measure,

[11] Again results for monthly data are in line with our conclusions and are reported in Table 8 in the Appendix.

Table 3
Sias herding measures for the *Crisis period (≥08/09/07)*

This table reports correlations and decomposed correlations in percentage terms considering only the period from 8 August 2007 until 30 March 2009. See notes in Table 2 for further explanations.

	All Stocks	DAX 30	MDAX	SDAX
Average correlation				
Daily data	18.49 (0.43)	22.21 (0.87)	18.92 (0.68)	16.50 (0.74)
Observations	50,524	12,349	20,430	17,745
Quarterly data	25.64 (3.47)	28.95 (6.96)	18.04 (5.06)	26.80 (4.73)
Observations	773	90	297	296
Anonymous transactions	27.15 (0.45)	21.98 (0.88)	24.58 (0.70)	30.97 (0.80)
Observations	45,541	12,301	19,179	14,061
Follow own trades				
Daily data	8.99 (0.22)	1.90 (0.04)	3.16 (0.05)	5.05 (0.08)
Quarterly data	1.98 (0.47)	0.69 (0.20)	0.35 (0.60)	0.09 (0.90)
Follow trades of others				
Daily data	9.50 (0.22)	0.39 (0.04)	0.32 (0.05)	0.21 (0.08)
Quarterly data	23.66 (2.43)	2.51 (0.20)	2.43 (0.50)	3.46 (0.90)

results obtained from the dynamic Sias measure crucially depend on the frequency of the data. While at a daily frequency, the main part of the correlation, about 56.19% (=0.1012/0.1801), results from institutions that follow their own trades, herding is much more pronounced for quarterly data. In line with Sias (2004) and Choi and Sias (2009), our quarterly estimates imply that nearly the whole correlation (92% = 18.8/20.32) results from following other traders, i.e., herding.

Moreover, in sharp contrast to daily herding measures but very much in line with the empirical literature, quarterly herding measures tend to be higher for smaller stocks. This may indicate that the size-effects predicted by herding theory are more relevant for longer-term herding.

Finally, we investigated whether the evidence on Sias herding depends on the state of the market. Table 3 presents results for the average correlation and the decomposed correlation during the crisis-period. In particular for quarterly data, the Sias herding measures indicate a higher degree of herding during the crisis-period.

6. Conclusions

This paper contributes to the empirical literature on the short-term herding behaviour of financial institutions by analysing high-frequency investor-level data that directly identifies institutional transactions. Applying Lakonishok *et al.*'s (1992) herding measure to a broad cross-section of German stocks over the period from August 2006 to April 2009, we find an overall level of herding of 1.44% for all investigated financial institutions, which is statistically significant but quite low. In the same vein, the dynamic herding measure of Sias (2004) shows that trades of institutions are correlated over time. However, the main part of this correlation stems from institutions that follow their own trades and is not a consequence of herding.

If herding behaviour is amplified by insufficient information availability or information asymmetry, herding should be more pronounced in small stocks and in times of market stress. Using daily data, both theoretical predictions are not supported by herding measures obtained from investor-level data. In fact, we find that short-term herding is even more pronounced in large stocks and highly developed market segments. Moreover, daily herding measures have not increased since the beginning of the financial crisis.

Our data set allows us to explore the role of data availability for the evidence on herding. First, we calculate the herding measures for quarterly data. Interestingly, the resulting longer-term herding term measures partly lead to different conclusions. In line with the empirical literature using low-frequent data, quarterly herding measures are larger for smaller stocks. Moreover, the degree of quarterly herding has increased during the financial crisis. In a second exercise, we transform our data in anonymous transactions by ignoring all information about the investor. Following the empirical literature, we assume that institutional traders can be identified by large trades. According to our empirical results, herding measures based on anonymous transactions should be viewed with caution. The resulting herding measures not only exaggerate the degree of herding, they also provide spurious evidence in favour of increased short-term herding during the financial crisis.

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Appendix A. The Modified Sias Measure Capturing Size-Effects

With increasing number of investors, the 'following other trades' term in the standard decomposition of the Sias herding measure will increase much faster than the 'following their own trades' term. Moreover, the cross-sectional standard deviation of the buyers ratio tends to fall. Simply dividing the sample into larger and smaller stocks could therefore automatically result in a larger relative contribution of herding (following others) in large capitalisation stocks. In order to capture the distorting effect of the average number of traders on the herding measure calculated for a specific market segment, Sias (2004) introduces a modified decomposition of the correlation coefficient.

The size-adjusted contribution of traders 'following own trades' is

$$\frac{(D_{nit} - \bar{br}_t)(D_{ni,t-1} - \bar{br}_{t-1})}{N^*_{it}}, \tag{5}$$

where N^*_{it} is the number of institutions trading stock i in both time periods $t-1$ and t. The average 'herding contribution' for each stock i and time t only refers to traders who follow the trades of others:

$$\sum_{n=1}^{N_{it}} \sum_{m=1,m\neq n}^{N^*_{i,t-1}} \frac{(D_{nit} - \bar{br}_t)(D_{mi,t-1} - \bar{br}_{t-1})}{N_{it}N^*_{i,t-1}}, \tag{6}$$

where N_{it} is the number of institutions trading stock i in t and N^*_{it} is the number of other institutions trading stock i in time $t-1$. Note that the modified measures do not add to the overall correlation coefficient.

Appendix B. Tables

Table 4

Statistics on trading of institutions

The first part of the table reports the average of investigated institutions active in a specific stock on a specific day. The numbers are computed according to the daily trade imbalance of the institutions. The second part of the table reports the share that the investigated institutions have in the trading volume of a specific stock on a specific day averaged over all stocks and days in percentage terms.

	All	DAX 30	MDAX	SDAX
Average daily number of traders active				
Whole sample	25.14	50.79	23.41	10.78
<08/09/07	31.96	65.26	28.80	13.10
≥08/09/07	20.80	41.01	20.00	9.34
Average daily market share in percent				
Whole sample	51.00	45.97	51.00	54.30
<08/09/07	70.34	65.91	75.33	68.71
≥08/09/07	39.45	32.46	37.43	45.82

Table 5

Daily LSV measures – different minimum numbers of trader active

This table reports mean values of daily *HM* in percentage terms for the whole sample of stocks, for the sub-sample of DAX 30, MDAX and SDAX stocks considering different minimum numbers of traders active (0, 5, 10 or 20) for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days (but only for that cases were the respective minimum trader amount is given) and than averaged across the different sub-sample of stocks. Standard errors are given in parentheses.

	All Stocks	DAX 30	MDAX	SDAX
>0 trader	1.55 (0.02)	3.65 (0.04)	1.25 (0.04)	0.54 (0.05)
Observations	87,839	20,904	33,673	33,262

Table 5 (Continued)

	All Stocks	DAX 30	MDAX	SDAX
>5 trader	1.40 (0.02)	3.65 (0.04)	1.24 (0.04)	−0.03 (0.05)
Observations	83,842	20,901	33,616	29,325
>10 trader	1.71 (0.02)	3.63 (0.04)	1.30 (0.04)	0.06 (0.06)
Observations	69,474	20,900	31,864	16,710
>20 trader	2.57 (0.03)	3.62 (0.04)	1.74 (0.04)	0.77 (0.10)
Observations	42,385	20,201	19,116	3,068

Table 6

Daily Sias measures – different minimum numbers of trader active

This table reports values of the average correlation coefficient β according to Sias (2004) considering different minimum numbers of traders active (0, 5, 10 or 20) for each stock on each trading day. The correlations where first estimated with a cross-sectional regression for each day t and stocks i. The reported coefficients display the time-series average of the regression coefficients. The coefficients are estimated considering the whole sample of stocks as well as only DAX 30, MDAX, and SDAX stocks severalty.

	All Stocks	DAX 30	MDAX	SDAX
>0 trader	17.61 (0.26)	20.13 (0.67)	19.02 (0.54)	16.20 (0.54)
Observations	87,839	20,904	33,673	33,262
>5 trader	18.01 (0.53)	20.01 (0.68)	18.60 (0.53)	16.84 (0.53)
Observations	83,842	20,901	33,616	29,325
>10 trader	19.64 (0.14)	20.12 (0.67)	19.84 (0.52)	18.10 (0.83)
Observations	69,474	20,900	31,864	16,710
>20 trader	18.72 (0.17)	20.02 (0.69)	19.29 (0.75)	14.04 (1.70)
Observations	42,385	20,201	19,116	3,068

Table 7

LSV herding measures – monthly data

This table reports mean values of *HM* in percentage terms, calculated at monthly frequency, see Table 1 for further explanations.

	All Stocks	DAX 30	MDAX	SDAX
Sample period: July 2006 – March 2009				
Monthly data	1.97 (0.07)	3.03 (0.16)	1.98 (0.14)	1.29 (0.17)
Observations	4,171	990	1,597	1,584

Table 7 (Continued)

	All Stocks	DAX 30	MDAX	SDAX
Pre-crisis period (<08/09/07)				
Monthly data	1.36 (0.12)	3.00 (0.22)	1.05 (0.18)	0.65 (0.22)
Observations	1,710	410	650	650
Crisis period (≥08/09/07)				
Monthly data	2.39 (0.13)	3.06 (0.23)	2.62 (0.20)	1.73 (0.24)
Observations	2,461	580	947	934

Table 8
Sias herding measures – monthly data

This table reports results for the Sias measure calculated at monthly frequency, see Tables 2 and 3 for further explanations.

	All Stocks	DAX 30	MDAX	SDAX
Sample period: July 2006 – March 2009				
Average correlation				
Monthly data	22.00 (1.50)	23.09 (2.48)	19.90 (2.43)	21.90 (2.47)
Observations	4,005	928	1,546	1,531
Follow own trades				
Monthly data	4.60 (0.45)	1.31 (0.10)	0.98 (0.23)	1.19 (0.53)
Follow trades of others				
Monthly data	17.40 (1.23)	1.95 (0.15)	2.22 (0.33)	2.98 (0.53)
Crisis period (≥08/09/07)				
Average correlation				
Monthly data	24.96 (1.95)	30.91 (4.06)	22.27 (3.12)	23.38 (3.16)
Observations	2,433	551	942	940
Follow own trades				
Monthly data	4.51 (0.47)	1.35 (0.32)	1.12 (0.40)	1.20 (0.50)
Follow trades of others				
Monthly data	20.45 (2.43)	2.45 (0.30)	2.13 (0.28)	3.16 (0.48)