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Herding of Institutional Traders

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Abstract

This paper sheds new light on herding of institutional investors by using a unique and superior database that identifies every transaction of financial institutions. *First*, the analysis reveals herding behavior of institutions. *Second*, the replication of the analysis with low-frequent and anonymous transaction data, on which the bulk of literature is based, indicates an overestimation of herding by previous studies. *Third*, our results suggest that herding by large financial institutions is not intentional but results from sharing the same preference and investment style. *Fourth*, a panel analysis shows that herding on the sell side in stocks is positively related to past returns and past volatility while herding on the buy side is negatively related to past returns. In contrast to the literature, this indicates that large financial institutions do not show positive feedback strategies.

Keywords: Investor Behavior, Institutional Trading, Stock Prices

JEL classification: G11, G24, C23

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1 Introduction

A growing literature has established the tendency of investors to accumulate on the same side of the market, called herding behavior. This kind of trading pattern is often held responsible for the destabilization of stock prices, increasing price volatility and the threatening of financial market stability, see e.g. Scharfstein and Stein (1990), Hirshleifer and Teoh (2003) or Hwang and Salmon (2004). The theory suggests several kinds of herd behavior, defined by the various explanations of the comovement. Under the common categorization, see e.g. Bikhchandani and Sharma (2001), herding is segregated into sentiment-driven *intentional herding* and *unintentional herding* driven by fundamentals. The distinction of the different sources of herding is crucial for regulatory purposes and to determine whether herding leads to market inefficiency or the emergence of financial bubbles.

The aim of this paper is to shed more light on the herding behavior of institutional investors, including banks and other financial institutions. Due to the dominance of this class of investors in the stock market, institutions indeed have the ability to move the market and impact prices, even more, if they herd. This potential emphasizes the importance to investigate *first* whether they herd and *second* the determinants of the herding behavior.

The previous literature on institutional herding has been severely handicapped by the availability of data. The studies rely either on *low frequent data* or on *anonymous transaction data*.

Empirical assessment of herding requires disaggregated investor-level data. In general, positions of institutions are, if at all, reported on very *low frequency*. For example in the case of U.S. mutual funds, reports of holdings are available on a quarterly basis, see e.g. Wermers (1999). For German funds, semi-annual reports are required, see Walter and Weber (2006). Using such low frequent data does not allow to capture trades that are completed within the period and does not reveal herding if it occurs within a shorter time interval. Such studies are also limited in investigating the determinants of herding.

There is no resolution on intra-quarter covariances of trades and returns. Thus, studies fail to conclude whether institutions are *reacting* to stock price movements or *causing* price movements, see Lakonishok, Shleifer and Vishny (1992).

Studies including Barber, Odean and Zhu (2009) try to overcome the problem of data frequency by using *anonymous transaction data* instead of reported holdings. However, those data do not allow an identification of the trader. Therefore, these papers follow the procedure to separate trades by size and identify trades above a specific cutoff size as institutional. While large trades are almost exclusively the province of institutions, institutions with superior information will split their trades to hide their informational advantage. Moreover, these studies are unable to identify the type of institution and thus cannot built up sub-samples of traders.

The dataset used in this paper overcomes these limitations. The paper utilizes a new dataset, including high-frequent investor-level data directly identifying institutional transactions. The analysis provides new evidence on the short-term herding behavior of financial institutions for a broad cross section of stocks over the period from July 2006 until March 2009. Moreover, this paper offers the first empirical investigation of herding by banks and other financial institutions in the German stock market.

By replicating the analysis with low-frequent data as well as with cutoff levels, results imply an overestimation of herding by previous studies. As second contribution, advancing on previous descriptive approaches, daily data combined with a panel analysis allow the investigation of possible sources of herding. The results reveal that financial institutions indeed show herding behavior and this herding depends on stock characteristics as well as on past returns and volatility of stocks. In particular, we find -contrary to previous evidence- that herding is more pronounced in larger and more liquid stocks. The mean herding measure for the 30 most professional institutions in DAX 30 stocks constitutes 5.17%. Moreover, herding on the sell side is positively related to past returns and past volatility while herding on the buy side is negatively related to past returns. These new results can be explained by *unintentional* herding that results from sharing the same investment style and risk models.

The rest of the paper is structured as follows: Section 2 reviews the theory behind herding behavior and Section 3 summarizes the previous literature. Section 4 introduces the data and Section 5 discusses the herding measure. Section 6 presents the empirical analysis. Section 7 offers a summary of the main results and concluding remarks.

2 Herding Theory

2.1 Types of Herding

2.1.1 Intentional vs. Unintentional Herding

The term 'herding' describes the tendency of institutions or individuals to show similarity in their behavior and thus acting like a herd. The theory suggests several kinds of herd behavior, defined by the various explanations of the comovement. Under the common categorization, see e.g. Bikhchandani and Sharma (2001), herding is segregated into *intentional herding* and *unintentional* or *spurious herding*.

Unintentional herding is mainly fundamental driven and arises because institutions may examine the same factors and receive correlated private information, causing them to arrive at similar conclusions regarding individual stocks, see e.g. Hirshleifer, Subrahmanyam and Titman (1994). Moreover, professionals may constitute a relative homogenous group. They share a similar educational background and professional qualifications and tend to interpret informational signals similarly.

From an macroeconomic perspective, unintentional herding can be an efficient outcome if it is driven by fundamentals. In contrast, intentional herding is generally considered as inefficient. Intentional herding is more sentiment-driven and refers to the imitation of other market participants resulting in simultaneous buying or selling the same stocks regardless of prior beliefs or information sets. This herding can lead to asset prices failing to reflect fundamental information, exacerbate volatility, destabilize markets and thus may give rise or contribute to bubbles and crashes on financial markets, see e.g. Scharfstein and Stein (1990), Shiller (1990), Morris and Shin (1999) or Persaud (2000).

From a psychological viewpoint, the impetus underlying imitation has often been assumed to stem from the human nature itself, in the sense that people may tend towards conformity (Hirshleifer (2001)) as a result of their interactive communication. Yet, intentional herding might be rational from the traders perspective and can be attributed to several factors leading to two major theoretical models.

2.1.2 Models of Intentional Herding

Information Cascade Model

According to the *information cascade model* (Bikhchandani, Hirshleifer and Welch (1992), Banerjee (1992) and Avery and Zemsky (1998)) trader copy the investment activities of other market participants because they might infer (from observed trading behavior) that the others have relevant information, resulting in the formation of informational cascades. This might be the case, if the trader himself possesses no information or he considers his own information as uncertain and regards the others as better informed. The trader might ignore his information, even if this information is superior, because it is not strong enough to reverse the decision of the crowd. However, under this model, herding mainly occurs in the short-term, since the arrival of public information and price adjustments will stop 'incorrect' information cascades. This is especially the case in developed capital markets. Advanced regulatory frameworks generally ensure the efficient flow of information to the market. Due to higher turnovers in developed markets information is usually timely incorporated into asset prices, thus rendering them more informative.

Reputation Based Model

Another set of rational herding incentives relates to the *reputation based model* originally developed by Scharfstein and Stein (1990). According to this considerations, institutions or professional investors are subject to reputational risk when they act differently from the crowd. Thus, they may ignore information they possess and imitate the decisions of the majority. Professionals are subject to periodic evaluation that often occurs against each other. Thus, at least traders with lower reputation face the incentive to imitate the higher reputed ones. Overall, traders might perceive the risk from potential failures higher compared to the benefits from a potential success if they go alone (Graham (1999)). Scharfstein and Stein (1990) call this effect 'sharing the blame'.

These models of *intentional herding* are closely related to each other and result both from the starting point that there is only little reliable information in the market and the trader are uncertain about their decision and thus follow the crowd. In contrast, in the case of *unintentional herding*, trader recognize public information as reliable, interpret them similar and thus end up at the same side of the market. Therefore, all types of herding are linked to the uncertainty or availability of information.

2.2 Revealing the Type of Herding

The distinction of the different sources of herding is crucial for regulatory purposes and to determine whether herding leads to market inefficiency. But the empirical discrimination of the different kinds is difficult because the number of factors that may influence an investment decision is very ample and the motives behind a trade are not discernable. The empirical literature sheds light on the determinants of herding by considering the link between herding and information or uncertainty and by using variables that proxy e.g. information availability.

Lakonishok et al. (1992) and Wermers (1999) segregate stocks by size. *Market capitalization* 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 for *intentional herding*.

As *unintentional herding* arises due to the simultaneous reaction on common signals, a manifestation of this kind of herding is momentum investment, i.e. *positive feedback trading*. If herding is driven by past returns, i.e. all react on price signals, this would be interpreted as evidence for unintentional herding (see Froot, Scharfstein and Stein (1992)).

Even though herding resulting from correlated positive feedback trading is considered as informed herding according to the theory above, such herding might also have an destabilizing impact on financial markets. Short-term strategies based on past returns, see e.g. De Long, Shleifer, Summers and Waldmann (1990), imply pro-cyclical behavior that aggravates downward or upward pressures in the market.

Persaud (2002) argues that market-sensitive risk management systems used by banks such as Value at Risk (VaR) models require banks to sell when prices decline and/or volatility rises. Thus, banks act like a herd, selling the same stocks at the same time in response to negative shocks. Although, this kind of trading is considered as *unintentional herding*, it leads to further slumps in prices. This is not offset by other classes of investors, causing destabilization and a lack of liquidity on equity markets. As institutions are increasingly using the same VaR models, as this is forced by regulators claiming high and common standards, the tendency is convergence of the market participants behavior. The market-sensitive risk management systems reduce the diversity of decision rules. Therefore, Persaud (2002) recommends regulators not to neglect the macro-prudential aspects of risks and incentive diversity of behavior among the market participants, through the use of different risk management systems.

3 Related Empirical Literature

3.1 First Evidence

One of the earliest work related to herding was that of Kraus and Stoll (1972) who analyzed parallel trading on a monthly basis among institutional investors such as mutual funds and banks and concluded that the institutions do not tend to trade in parallel with one another. Lakonishok et al. (1992) adapted the main idea and constructed a herding measure that has become a standard in the empirical literature.[1] Lakonishok et al. (1992) test for herd behavior within a quarterly time span using a sample of US equity funds covering the period 1985 to 1989. They find only low values of herding for their overall sample.

3.2 Size and Performance of Stocks

Lakonishok et al. (1992) constructed also subsamples based on past performance and the size of the stocks. While different past performances of stocks did not lead to significant higher herding measures, they find evidence of herding being more intense among small companies compared to large stocks. Contrary, Grinblatt, Titman and Wermers (1995) find a relation between past performance and herding. They documented that positive feedback strategies are employed by the majority of the 274 US mutual funds analyzed, that demonstrated herding behavior in the 1975-1984 period. Further empirical evidence on the link between herding, size and performance is provided by Wermers (1999) who presents a slightly higher level of herding than Lakonishok et al. (1992) for a comprehensive sample of US mutual funds during 1975-1994. He also found higher herding measures for small stocks and for funds following positive feedback strategies. Wylie (2005) also applies the measure proposed by Lakonishok et al. (1992). In contrast to the US studies, he found for UK mutual funds over the period from 1986 to 1993, that funds herd out of stocks that have performed well in the past.

3.3 Development of the Market

Walter and Weber (2006) report significant positive and higher levels of herding for German mutual funds compared to the US research based on semi-annually data. Another study analyzing German fund herding is Oehler and Wendt (2009) finding herding on a semi-annually basis in the period from 2002-2005. Walter and Weber (2006) link the finding of herding to the stage of development of the financial market. They argue

[1] The measure of Lakonishok et al. (1992) is explained in Section 5.

that the German market is not as highly developed as the US and UK capital markets. In relation, other studies show the existence of higher herding levels in emerging markets compared to developed ones. For example, Lobao and Serra (2007) document strong evidence of herding behavior for Portuguese mutual funds. Significant herding is also analyzed for Indonesia (Bowe and Domuta (2004)), Poland (Voronkova and Bohl (2005)), Korea (Choe, Kho and Stulz (1999), Kim and Wei (2002)) and South Africa (Gilmour and Smit (2002)).

Such 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, hamper reliability of public information and thus fundamental analysis, see Antoniou, Ergul, Holmes and Priestley (1997) and Gelos and Wei (2002). Kallinterakis and Kratunova (2007) argued that in such an environment it is reasonable to assume that investors will prefer to base their trading upon their peers' observed actions. Thus, intentional herding through information cascades is more likely to occur in less developed markets.

3.4 State of the Market

There is also evidence revealing that herding behavior can depend on the state of the overall market. Choe et al. (1999) found for the Korean stock market higher herding levels before the Asian crisis of 1997 than during the crises. Hwang and Salmon (2004) find more evidence of herding during relatively quiet periods than during periods when the market is under stress, using data from US and South Korean stock markets. In contrast, the results of Bowe and Domuta (2004) indicate that herding of foreigners increased following the outbreak of the crisis using data from Jakarta Stock Exchange. Borensztein and Gelos (2003) found significant herding of funds but no variation between crisis and non-crisis periods investigating the Czech and Asian Crisis in 1997, Russian ruble collapse in 1998 and Brazilian devaluation in 1999.

4 Data and Sample

4.1 Data Problems of Previous Literature

The previous literature on herding reviewed above is severely handicapped by the availability of data. The studies rely either on holding positions of institutions or on anonymous transaction data.

4.1.1 Low Frequency

The first group of studies identifies institutional transactions as changes in reported positions in a stock. However, positions are reported, if that, on a very low frequency. Most studies focus on mutual funds as institutions. In the US those funds generally report on a quarterly basis. For German mutual funds, half-year reports are required.[2] Semi-annual and also quarterly data provide only a crude basis for inferring trades and the frequency is especially too low in a rapid changing stock market environment. On the one hand, herding might be understated, since trades that are completed within the period are not captured and herding is not revealed if it occurs within a shorter time interval. Moreover, the theory predicts that intentional herding arises due to informational cascades. However, in markets with frequent public information flows and higher turnovers that lead to the timely incorporation of information, informational cascades are likely to occur only in the short-term, until public information arrive in the market. On the other hand, in longer time intervals, herding might also be overstated 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. For long time intervals, the concepts of parallel and imitative behavior are severely stretched, probably beyond the level that causes concern. The studies are also limited in investigating the determinants of herding. It may be difficult to correlate herding measures with stock specific characteristics that change throughout the quarter. In particular there is no resolution on intra-quarter

[2] 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.

covariances of trades and returns, thus studies fail to conclude whether institutions are reacting to stock price movements or causing price movements, see Lakonishok et al. (1992).

4.1.2 Identification of Trader

The second set of studies are forced to make assumptions on the person behind the trade. They use a naive cutoff approach to determine institutional trades. Transactions above a specific cutoff size are considered as proxy for institutional trades, since large trades might be the province of institutions. For example, Lee and Radhakrishna (2000) suggest a cutoff of \$50,000 for larger stocks. However, institutions could split their trades to hide a possible superior information advantage. Thus, the most informative institutional trades are not likely to be the largest. In fact, our dataset suggests that institutions trade often during a day but not necessarily at those large amounts. Although, since trades below \$5,000 are regarded as retail trades according to Lee and Radhakrishna (2000), a large number of trades (between the range) remain unclassified.

4.2 Description of the Database

This study overcomes these problems by using disaggregated high frequent investor-level data. 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). According to 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 organized market. Currently, about 4,000 institutions report their trades.

These records enable us to identify all relevant trade characteristics. In particular the trader (the identification of the institution), the particular stock, time, number of traded shares, price and the volume of the transaction. Moreover, the records identify on behalf of whom the trade was executed, i.e. whether the institution trade for its own account or in connection with an investment service on behalf of a client that is not a financial institution. Since the aim of our study is the investigation of institutional trades, in particular, the trades of financial institutions, we will focus on the trading of own accounts, i.e. if a bank or an financial services institution is clearly the originator of the trade. The direct identification of the trading financial institution also enables us to built subgroups of institutions in order to examine differences in their behavior.

Using data from July 2006 until March 2009, and thus 698 trading days, we cover market upturns as well as the recent market downturn. We will investigate whether trading behavior has changed according to the market turmoil.

The analysis focuses on the shares included in the three major German stock indices, i.e. the DAX 30 (the index of the thirty largest and most liquid stocks), the MDAX (a mid-cap index of fifty stocks that rank behind the DAX 30 in terms of size and liquidity) and the SDAX (a small-cap index of fifty stocks that rank behind the MDAX components). Those values allow to distinguish between trading behavior in small and large stocks. Over the observation period we possess in those stocks overall 167,422,502 records of the proprietary transactions of 1,120 institutions on German stock exchanges. Following the related literature using daily data, for each institution we compute the daily trade imbalance.

The stocks were selected according to the index compositions at the end of the observation period at 31 March 2009. The time series of 5 stocks of the MDAX and 5 stocks of the SDAX are not complete for the whole period. We have therefore an unbalanced panel of stocks and days with overall 88,435 observations.

5 Do Institutions Herd?

5.1 The Herding Measure

Following the empirical literature on herding behavior, we use the herding measure introduced by Lakonishok et al. (1992). According to this 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 could be expected if they traded independently.

A starting point of the herding measure is the assumption that under the null hypothesis of no herding, the decision to buy and to sell is a bernoulli distributed random variable with equal success probability for all stocks at a given time period.[3]

Consider a number of n_{it} institutions trading in stock i on time t. Out of these n_{it} transactions, a number of b_{it} are buy transactions. The buyers ratio br_{it} is then defined as $br_{it} = \frac{b_{it}}{n_{it}}$. The random variable b_{it} is binomially distributed.

The probability p_{it} that an institution buys stock i in t is determined by the overall probability to buy in time t for all stocks $\bar{br}_t$ and additionally by the degree of herding h_{it} in the specific stock i in t:

$$p_{it} = \bar{br}_t + h_{it}. \tag{1}$$

Consequently, under the null of no herding, $p_{it} = \bar{br}_t$, i.e. the probability to buy the specific stock i in t corresponds to the overall probability to buy ($\bar{br}_t$) in time t. The number of buys in stock i in time t is then the result of n_{it} independent draws from a bernoulli distribution with probability $\bar{br}_t$ of success.

The buy probability $\bar{br}_t$ results from an overall signal in the market at time t. It is measured as the expected value of the buyers ratio in t, $E_t[br_{it}] = \bar{br}_t$, i.e. the period average of the buyers ratio and thus the number of net buyers in t aggregated across all stocks i divided by the number of all traders in t:

$$\bar{br}_t = \frac{\sum_{i=1}^{I} b_{it}}{\sum_{i=1}^{I} n_{it}}. \tag{2}$$

Under these assumptions, herding (h_{it}) is defined as a deviation from the overall buy probability during t, i.e. as excess dispersion of what would be expected for that time.

[3] One implication of this assumption is that short selling must be possible. This assumption is not problematic for our investigated institutions, for which short selling is in general feasible. In contrast, most mutual funds investigated by previous studies, are not allowed to undertake short sales. Thus, if they have no holding in stock i, they can only be a buyer and the actions would not be binomially distributed.

Therefore, the measure captures similar trading patterns beyond the market trend and eliminates the influence of market-wide herding.

The traditional herding statistic proposed by Lakonishok et al. (1992) is given by

$$HM_{it} = |br_{it} - \bar{br}_t| - E_t[|br_{it} - \bar{br}_t|]. \tag{3}$$

The first term captures the deviation of the buyers ratio in i and t from the overall buy probability during t. The latter term $E_t[|br_{it} - \bar{br}_t|]$ is the expected value of the difference between buyers ratio and period-average buyers ratio.

Under the assumption that the number of buys b_{it} is binomially distributed with probability $\bar{br}_t$ and n_{it} independent draws it is given by

$$E_t[|br_{it} - \bar{br}_t|] = \sum_{k=0}^{n_{it}} \binom{n_{it}}{k} \bar{br}_t^k (1 - \bar{br}_t)^{n_{it}-k} |\frac{k}{n_{it}} - \bar{br}_t|. \tag{4}$$

Subtracting this term, accounts for the possibility to observe more variation in the buyers ratio in stocks with only few trades, since buy decisions are stochastic. The variance of br_{it} depends on n_{it} and rises as the number of traders declines. Then, even if no herding exist the absolute value of $|br_{it} - \bar{br}_t|$ is likely to be greater than zero. Doing this adjustment, the herding measure HM_{it} gets zero if the trades are independent. The adjustment term declines as n_{it} rises.[4]

The empirical literature following Lakonishok et al. (1992), calculates the mean across all stocks and all periods, leading to the mean herding measure $\overline{HM}$. A positive and significant value of $\overline{HM}$ then 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 a $\overline{HM}$ of 2% indicates that for a given stock in one day, out of every 100

[4]Following previous studies, e.g. Wermers (1999), HM_{it} is only computed if at least 5 traders are active in i at time t, leading to a loss of observations and an unbalanced panel. However, Table 6 in the Appendix shows that even in the SDAX stocks on average 10.78 institutions are active each day. 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 5 traders, we loose 3,997 observations for the sample of all institutional trader, i.e. 83,842 observations remain. Tables 11 and 12 in the Appendix display results with different minimum traders and reveal that results are robust with respect to the presumed minimum traders.

transaction, 2 more trader 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 $\overline{HM}$ is not equal to one, even if all traders buy stock i during 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 the market trend are analyzed.

The herding measure HM_{it} gauges herding without regard to the direction of the trades (buy or sell). Following Grinblatt et al. (1995) and Wermers (1999), we also determine 'buy herding' BHM_{it} and 'sell herding' SHM_{it}, to distinguish whether institutions buy or sell a stock i in herds. The sample is therefore separated in $BHM_{it} = HM_{it}$ if $br_{it} > \bar{br}_t$ and $SHM_{it} = HM_{it}$ if $br_{it} < \bar{br}_t$. Note that $br_{it} = \bar{br}_t$ is not captured by BHM_{it} or SHM_{it} because in this case no herding exist, i.e. herding is neither on the buy nor on the sell side.[5]

The discrimination between BHM_{it} and SHM_{it} is useful if institutions show asymmetry in their behavior on the buy and sell side. The separate measurement of herding *into* stocks and *out* of stocks becomes even necessary when analyzing the determinants of their trading behavior in Section 6.2.

5.2 Preliminary Statistics on Herding

5.2.1 Overall Sample

Our sample comprises 1,120 institutional traders, active in the investigated stocks during our observation period. Among these, 1,044 institutions trade in the DAX 30 stocks, 742 in the MDAX stocks and 512 in the SDAX stocks. These institutions have an average daily market share in DAX 30 stocks of about 46%. Interestingly, the market share declined after the start of the recent financial crises, implying a retraction from trading business. In the period from 01 July 2006 until 08 August 2007 the proportion

[5] Comparing the observations in e.g. Table 5, the loss of data is not empirically relevant.

constituted 66%, shrinking to 32% after 09 August 2007. Table 6 in the Appendix provides further summary statistics.

Table 1: Mean Daily Herding Measures (1)

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.40 (0.02)	1.36 (0.04)	1.45 (0.04)	3.65 (0.04)	3.42 (0.06)	3.85 (0.06)
Observations	83,842	42,193	41,644	20,901	9,990	10,910
$<$08/09/07	1.32 (0.04)	1.29 (0.05)	1.27 (0.05)	4.35 (0.06)	4.23 (0.09)	4.46 (0.08)
Observations	33,257	16,832	16,425	8,427	4,106	4,321
$\geq$08/09/07	1.60 (0.03)	1.38 (0.05)	1.58 (0.05)	3.17 (0.06)	2.86 (0.08)	3.45 (0.08)
Observations	50,585	25,361	25,219	12,474	5,884	6,589

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering all institutions in the sample. Standard errors are given in parentheses. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks.

Our results regarding overall herding are presented in Table 1. The mean value of the herding measure $\overline{HM}$ at daily frequency over the complete period and over all stocks in our datasample is 1.40%. The value is statistically significant but small and slightly lower than in previous studies using low frequency data, e.g. Lakonishok et al. (1992) or Walter and Weber (2006) who both found herding about 2.70%.

We found a significantly higher herding measure in DAX 30 stocks. Considering only stocks in this major German index, the mean herding measure is 3.63%, i.e. about 2.5 times larger than in the whole sample. Therefore, in contrast to previous findings, e.g. Wermers (1999) or Lakonishok et al. (1992), who report that correlated trading is higher in small stocks, our sample institutions herd into and out of large stocks. Table 7 in the Appendix shows that daily herding measures for MDAX stocks are significantly lower, i.e. 1.24% and daily herding in SDAX is even insignificant. This result is also contradicting to the theory of *intentional herding* which predicts higher herding levels in stocks with less information availability and asymmetry. The herding behavior might therefore more likely fall in the category of *unintentional herding*.

We also consider different periods for the computation of the average herding measure to investigate whether herding varies between the crisis and non-crisis period. 09 August 2007 is widely considered as starting point of the financial crises, manifesting in tensions in the European money market leading to a rapid increase of the overnight rate at this date, owing to the liquidity impasses caused by the problems in the US subprime mortgage loan market.

Differentiating across these non-crisis and crisis periods reveals that herding exists in both periods. In line with the mixed evidence in the previous literature, see Section 3, our results are not uniform. We find slightly higher evidence for herding in DAX 30 stocks before the financial crises but herding in MDAX and SDAX stocks is higher during the crises. However, the difference between buy and sell herding suggests, that institutions more likely herd out of stocks during the crises period. This might be a result of higher volatility of stocks in the financial crisis but could also be related to lower or negative returns of the stocks, suggesting positive feedback trading. Empirical analysis discussed in Section 6.2 will shed light on this issue.

5.2.2 The Role of Low-Frequency and Cutoff Size

The bulk of the literature on herding is forced to rely either on lower frequency data or to use transaction data and make assumptions regarding the identity of the trader using a cutoff approach to determine institutional trades. For the sake of comparison and to shed more light on the impact of these data limitations on the herding measure, we re-calculate the measures constraining our sample to quarterly data and to trades above a specific size.

Simulation with Low-Frequency

Table 2: Mean Quarterly Herding Measures (1)

	All Stocks			DAX 30		
	HM	*BHM*	*SHM*	*HM*	*BHM*	*SHM*
Whole sample	2.29 (0.15)	2.09 (0.19)	2.49 (0.23)	3.59 (0.26)	3.29 (0.34)	3.91 (0.42)
Observations	1,395	688	707	331	170	161
<3.Q./07	1.63 (0.20)	1.92 (0.31)	1.35 (0.27)	2.98 (0.41)	2.84 (0.64)	3.12 (0.53)
Observations	523	260	263	123	61	62
≥3.Q./07	2.69 (0.20)	2.19 (0.25)	3.16 (0.32)	3.95 (0.35)	3.54 (0.40)	4.40 (0.60)
Observations	872	428	444	208	109	99

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering all institutions in the sample. The measures are calculated considering a minimum number of 5 traders for each stock during the quarter. The herding measures are first computed over the whole sample stocks and over all quarters and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Instead of using the daily trade imbalance of a specific institution, we calculate the monthly and the quarterly trade imbalances. In line with previous studies using quarterly data e.g. Lakonishok et al. (1992) or Wermers (1999), results displayed in Table 2 reveal that herding measures are higher on a quarterly horizon. Comparing daily, monthly and quarterly results (see also Tables 13 - 15 in the Appendix), the herding measure rises when the frequency gets lower, indicating a slightly overestimation of herding measures when using low frequency data.

Simulation with Cutoff Size

Following studies that use cutoff approaches to identify institutional transactions (e.g. Barber et al. (2009)), we drop institutional trades from our sample that are below a

Table 3: Mean Daily Herding Measures - Cutoff Size (1)

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	4.58 (0.02)	4.45 (0.04)	4.71 (0.04)	4.39 (0.04)	4.34 (0.05)	4.43 (0.05)
Observations	80,012	39,882	40,129	20,865	10,353	10,511
<08/09/07	2.54 (0.03)	2.55 (0.04)	2.54 (0.04)	2.47 (0.03)	2.41 (0.04)	2.53 (0.04)
Observations	32,751	16,894	15,857	8,426	4,165	4,261
≥08/09/07	5.99 (0.04)	5.86 (0.06)	6.12 (0.06)	5.68 (0.05)	5.64 (0.08)	5.73 (0.08)
Observations	47,261	22,988	24,272	12,439	6,188	6,250

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering all institutions in the sample but dropping transactions below €34,000 for DAX stocks, €14,000 for MDAX stocks and €7,000 for SDAX stocks. Standard errors are given in parentheses. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks.

specific size. Lee and Radhakrishna (2000) suggests the cutoffs of \$50,000, \$20,000 and \$10,000 for large, medium, and small stocks. Assuming the current level of exchange rates, we adopt the main idea and consider only trades in DAX stocks, MDAX stocks, 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 loose 118,307,150 due to those cutoffs. We ignore the identification of the trader, thus treating every remaining transaction independently, i.e. if the same institution trades more than one time during a day, those transactions are regarded as trades of different institutions.

The results for the mean daily herding measures are displayed in Table 3 and for MDAX and SDAX stocks in Table 16 in the Appendix. The calculated means now reveal much higher herding levels, suggesting an overestimation of herding when using a cutoff approach. Moreover, herding is much more pronounced during the crises period. The difference between buy and sell herding is quite small, suggesting a high correlation of large buy trades as well as large sell trades during the crises. Overall, the results of the re-calculations indicate that earlier literature might have overestimated the herding level.

5.2.3 Subgroups of Institutions

The theory of *unintentional herding* predicts higher herding levels among institutions which share the same investment style and same professional qualifications (see Hirshleifer et al. (1994)). Moreover, according to the reputation based model higher *intentional herding* can be expected in a more homogenous group of professionals that are evaluated against each other (see Scharfstein and Stein (1990)). The overall sample investigated in Section 5.2.1 contains a large heterogeneous group of institutions. It might be more interesting to investigate herding into subgroups of institutions.

Among the 1,120 institutions, the 30 most active traders, according to their trading volume in the investigated shares, account for 80% of the whole trading volume over all institutions and can thus be regarded as most professional and most important for the stock market. These professionals can be considered as belonging to the same peer group.

Building a subsample according to trading activity reveal a higher herding measure for the 30 most active traders, see Table 4.[6] The mean daily herding measure across all stocks is 2.6%. There is evidence for more herding on the buy side in the non-crisis period and higher herding on the sell side during the crisis. This might be a result of higher volatility of stocks in the financial crisis but could also be related to lower or negative returns of the stocks, suggesting positive feedback trading. Empirical analysis discussed in Section 6.2 provides more insights.

[6]Note that considering a subgroup of 30 institutions instead of e.g. 10 ensures that enough traders are active in a specific stock on a specific day. Nevertheless, 14,879 observations are lost, i.e. 68,963 observations remain.

Table 4: Daily Herding Measures of 30 Most Active Traders (1)

	All Stocks			DAX 30		
	HM	*BHM*	*SHM*	*HM*	*BHM*	*SHM*
Whole sample	2.48	2.67	2.30	5.18	5.28	5.08
	(0.03)	(0.05)	(0.05)	(0.06)	(0.08)	(0.08)
Observations	68,963	35,806	33,130	20,853	10,692	10,154
<08/09/07	2.93	3.55	2.15	5.84	6.26	5.35
	(0.05)	(0.07)	(0.08)	(0.08)	(0.12)	(0.12)
Observations	30,362	16,868	13,494	8,427	4546	3,881
≥08/09/07	2.14	1.87	2.41	4.73	4.55	4.92
	(0.05)	(0.07)	(0.07)	(0.08)	(0.12)	(0.12)
Observations	38,601	18,938	19,636	12,426	6,146	6,273

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering only the 30 most active institutions in the sample. These 30 institutions are identified according to their overall trading volume over the whole sample period and all sample stocks. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Considering DAX 30 stocks, the herding measure even rises to 5.17%. This can be interpreted as a high level of herding compared to previous findings. Also for MDAX and SDAX stocks the herding measure is higher as for the whole group of institutions, but still small, see Table 8 in the Appendix.

The subgroup of 30 most active traders includes a few financial institutions other than banks (i.e. financial service institutions) and also foreign investment banks. We build another subsample comprising only the 40 most active German banks that are engaged in proprietary trading on stock markets.[7] Those banks are subject to the same regulatory regime and oversight by the financial authority. Although, the regulatory

[7]We select those institutions according to their trading volume over the observation period in the selected stocks. We select only German institutions according to section 1 paragraph 1 of the German banking act. Note that we now use 40 instead of 30 to ensure that enough traders are active in a specific stock on a specific day. The sample than comprises 69,257 observations.

framework and risk management systems for the foreign banks are expected to be similar, for those German banks we were able to ensure -due to an investigation of the risk reports included in their annual reports- that they commonly use VaR models and implement regulatory or internal VaR limits.

The results shown in Table 9 in the Appendix are similar to that for the subgroup of 30. Again, the herding measure is much higher in DAX 30 stocks with a mean of 5.21%. In line with the results above, buy herding is higher in the pre-crises period while sell herding is more pronounced during the crisis. Results for MDAX and SDAX stocks are again significantly lower and get even insignificant in case of buy herding in SDAX stocks, see Table 10 in the Appendix. The analogy of the results suggests that both subgroups are similar homogenous.

6 Detecting the Determinants of Herding

6.1 Possible Determinants of Herding

Theory described in Section 2.1 predicts that herding behavior centers around information in the market. On the one hand *intentional herding* results from information asymmetry or information uncertainty. On the other hand *unintentional herding* is related to reliable public information. By investigating the sources of herding we will therefore especially focus on empirical proxies to measure information availability, information asymmetry or uncertainty in the market and on those determinants that may imply a destabilizing procyclicality.

First, following the previous literature on herdingwe use as one possible determinant the firm size ($Size$). Firms with small size are usually less transparent, i.e. less public information is available. The model of intentional herding would therefore predict an inverse relation between herding and firm size. Also previous evidence reviewed in Section 3 finds a higher herding level in smaller stocks. In contrast, our results in Section 5.2 indicated higher herding in larger stocks. Firm size is measured by the logarithm of previous day's closing market capitalization of the specific stock.

A *second* factor related to herding might be the trading volume (Vol) of a specific stock. A vast literature highlights the relation between information quality, market liquidity and information asymmetries. In particular, Diamond and Verrecchia (1991) predict higher information asymmetry in less liquid markets. The model of Suominen (2001) suggests that higher trading volume indicate better information quality. Leuz and Verrecchia (2000) and Welker (2006) argue that market liquidity could be measured by transaction volumes or bid-ask spreads. We will therefore use market volumes of stocks as proxy for information asymmetry and would expect from intentional herding theory that lower trading volumes are associated with higher herding levels.

Third, we compute stock return volatility (Std) based on the standard deviation of past 250 daily stock return.[8] On the one hand, stock return volatility is assumed to reflect the extent of disagreement among market participants thus proxy the degree of uncertainty in the market. Intentional herding models would therefore predict higher herding in stocks that experienced higher degree of volatility. Note that higher information uncertainty is equally likely to induce herding on both the buy and sell side. On the other hand, higher levels of herding in more volatile stocks might also be related to a common use of VaR models or other volatility sensitive models for risk management purposes and according to regulatory requirements, see Persaud (2002). The minimum observation period according to Basel II market risk standards is one year, i.e. 250 trading days. We therefore expect in our subsample of 30 most active traders more sell herding in stocks with higher past year standard deviation of stock returns, since those regulated institutions highly engaged in trading generally use such risk management models. Moreover, our subgroup of 40 German banks include exclusively banks using VaR models and implementing regulatory or internal VaR limits.[9] A positive impact of volatility on sell herding but not on buy herding could then be considered as unintentional herding.

Fourth, we consider past returns of stocks (r). As unintentional herding arises due to

[8] We also use past 90 and 30 stock returns to check robustness.

[9] According to statements in their risk reports included in annual reports.

the simultaneous reaction on common signals, a manifestation of this kind of herding is momentum investment. De Long et al. (1990) argued that institutions follow short-term strategies based on positive feedback trading and thus show pro-cyclical behavior. Such trading pattern could result in herding, i.e. if all react on the same price signals, see Froot et al. (1992).

6.2 Empirical Results of a Fixed Effects Panel Model

6.2.1 Empirical Determinants of Herding Behavior

To examine the relation between institutional herding and its possible determinants, we estimate the following fixed effects panel regression model:

$$HM_{it} = a + b|r_{i,t-1}| + cStd_{it} + dSize_{i,t-1} + eVol_{it} + \alpha_i + \gamma_t + \epsilon_{it}, \tag{5}$$

where HM_{it} is the herding measure as calculated according to equation (3). $|r_{i,t-1}|$ is the absolute value of the return of stock i measured from the closing prices on day $t-1$ and $t-2$. The absolute value is used since HM_{it} does not discriminate between the buy and the sell side. Std_{it} is the volatility, measured as standard deviation of past 250 daily stock returns. $Size_{i,t-1}$ is measured by the logarithm of previous day's closing market capitalization of the stock i. Vol_{it} captures the logarithm of the trading volume of stock i during the trading day t. α_i are heterogenous stock specific effects and γ_t are time dummies.[10]

We concentrate on the herding measures for the two more homogeneous subgroups of 30 most active traders and 40 most active German banks. We are especially interested whether their higher herding measures result from *unintentional herding* due to the same investment style or from *intentional herding* due to the belonging to the same peer group, see Section 2.1. Moreover, these institutions are the most relevant for the

[10] An F-test strongly suggests the inclusion of time dummies γ_t in the regressions and a Breusch-Pagan Lagrange Multiplier test on $H_0 : \sigma_i^2 = 0$ indicates the existence of individual effects α_i.

stock market. The detection of intentional herding or procyclical behavior within these groups would suggest a high potential hazard for financial stability.

Table 5: Fixed Effects Panel Regression - Herding of 30 Most Active Trader

	HM_{it}	BHM_{it}	SHM_{it}
Impact of Regressors			
$Size_{i,t-1}$	0.0020	0.0014	-0.0039^{*}
	(0.0027)	(0.0046)	(0.0023)
Vol_{it}	0.0069^{***}	0.0067^{***}	0.0087^{***}
	(0.0012)	(0.0017)	(0.0009)
$\|r_{i,t-1}\|$	-0.0001		
	(0.0003)		
$r_{i,t-1}$		-0.0014^{***}	0.0008^{***}
		(0.0002)	(0.0002)
Std_{it}	0.0031^{***}	-0.0011	0.0048^{***}
	(0.0012)	(0.0012)	(0.0012)
Diagnostics			
$Wooldridge$	$F = 0.346$	$F = 0.377$	$F = 0.385$
	($Prob > F$=0.5573)	($Prob > F$=0.5402)	($Prob > F$=0.5359)
$Cook - Weisberg$	$\chi^2 = 3383.14$	$\chi^2 = 4924.52$	$\chi^2 = 1290.95$
	($Prob > \chi^2$=0.0000)	($Prob > \chi^2$=0.0000)	($Prob > \chi^2$=0.0000)
$Sargan - Hansen$	$\chi^2 = 10.343$	$\chi^2 = 11.122$	$\chi^2 = 14.026$
	($Prob > \chi^2$=0.0350)	($Prob > \chi^2$=0.0252)	($Prob > \chi^2$=0.0072)
Observations	65,846	34,130	31,691

Notes: The herding measure HM_{it} for the subgroup of 30 most active traders is regressed on variables $Size_{i,t-1}$, Vol_{it}, $|r_{i,t-1}|$ and Std_{it}. The buy and sell herding measures BHM_{it} and SHM_{it} is regressed on variables $Size_{i,t-1}$, Vol_{it}, $r_{i,t-1}$ and Std_{it}. The variable $Size_{i,t-1}$ is the logarithm of market capitalization, Vol_{it} is the logarithm of the trading volume of stock, $r_{i,t-1}$ is the daily stock return and $|r_{i,t-1}|$ is its absolute value. Std_{it} measures the standard deviation of past 250 daily stock returns. The statistical significance at 1%, 5% and 10% is represented as ***, **, and * respectively. Standard errors are given in parentheses in the upper part of the table. The lower part of the table reports test statistics and p-values in parentheses. $Wooldridge$ and $Cook - Weisberg$ are tests on serial correlation and heteroscedasticity of error terms. $Sargan - Hansen$ displays the overidentification test on the independence of random effects.

The upper part of Table 5 shows the results of a fixed effects panel regression with 30 most active traders. Results for the 40 largest German banks are again similar and are displayed in Table 17 in the Appendix.

The results for the regression with the unsigned herding measure HM are displayed in the first column. The coefficient estimate for $Size$ is insignificant and the coefficient Vol is positive and statistically significant. First, this suggest that the evidence of higher herding levels for DAX 30 stocks in Section 5.2 is more likely to result from the higher liquidity of those stocks than from the higher market capitalization. Second, since higher trading volume is related to lower information asymmetry and higher information quality, see e.g. Diamond and Verrecchia (1991), this result suggests that those large financial institutions do less likely show *intentional herding*. The result could be an indication for characteristic herding, i.e. *unintentional herding*, whereby the institutions share a common investment style and prefer to buy and sell stocks with higher trading volume.

The parameter estimate for volatility of returns *Std*, measured as standard deviation of stock returns over the last year shows that *Std* has a positive impact on herding, indicating that there is more herding for more volatile stocks. Volatility in the market is related to uncertainty and thus, at first glance, this estimate provide an inconsistent story, since this is a hint on *intentional herding*. However, the estimate could also be related to the common use of risk management models that indicate selling of more volatile stocks. Results on buy and sell herding discussed subsequently will shed more light on this issue.

6.2.2 Empirical Determinants of Buy and Sell Herding

The variables described above might affect buy and sell herding in an asymmetric fashion. We therefore estimate the model (5) separately for herding on the buy and sell side with almost the same set of explanatory variables, except that the absolute return $|r|$ is replaced by signed return r as the direction of the recent price movement will affect whether momentum investors herd more on the buy or sell side:

$$BHM_{it} = a^b + b^b r_{i,t-1} + c^b Std_{it} + d^b Size_{i,t-1} + e^b Vol_{it} + \alpha_i^b + \gamma_t^b + \epsilon_{it}^b \qquad (6)$$

$$SHM_{it} = a^s + b^s r_{i,t-1} + c^s Std_{it} + d^s Size_{i,t-1} + e^s Vol_{it} + \alpha_i^s + \gamma_t^s + \epsilon_{it}^s \qquad (7)$$

The results for the fixed effects regressions on buy and sell herding are reported in the second and third column of Table 5. Estimates for Vol reveal that herding on the buy and sell side is positively related to the liquidity of stocks. Again market capitalization measured as $Size$ does not play an important role.

The results for r and Std are interesting: First, the coefficient estimate for Std on buy herding is negative but insignificant. In case of sell side herding Std has a significant positive impact. Hence, the higher the volatility of a stock, all the more herding occurs on the sell side. It is therefore unlikely that *intentional herding* occurs which results from uncertainty in the market, since this would equally effect buy and sell herding. Apparently, institutions share the preference to sell stocks that have shown a high volatility. This is a clear indication for *unintentional herding* that might be a result of risk management purposes, see Persaud (2002).[11]

The estimated impact of returns r are statistically significant for buy and sell herding regressions. As in case of Std the coefficient estimates are of opposite signs - i.e. buy herding is significantly negatively related to past returns, while past returns have a positive impact on sell herding. This contradicts the conclusions drawn in previous studies, e.g. Grinblatt et al. (1995), Wermers (1999) or Walter and Weber (2006) who claim that institutions are momentum investors and follow positive feedback strategies. In contrast, in our sample, institutions share the preference to buy past looser and sell past winner. Overall, the results indicate that herding occurs more *unintentionally* and results from sharing the same preferences and investment style.[12]

[11] The results are robust with respect to shorter periods for the calculation of the standard deviation. Using past 90 daily stock returns or past 30 daily stock returns do not change the results significantly. For brevity, these results are not presented and are available on request.

[12] We also included additionally lagged returns up to 5 trading days, $r_{i,t-2}$,..,$r_{i,t-5}$, in the regressions, to check whether further past returns influence herding. Our results do not change qualitatively. The coefficient estimates of all past returns have the same sign, i.e. are all negative in the buy herding

The lower part of Table 5 presents the relevant test statistics and p-values of diagnostic tests. The three models (5) - (7) were estimated as fixed effects panel regressions using the within estimator, i.e. the Ordinary Least Squares (OLS) of deviations from stock-specific means. This estimator is feasible, since according to a Hausman test on endogeneity of the regressors, the null hypothesis of exogeneity cannot be rejected. The OLS assumption of no serial correlation in the idiosyncratic errors, i.e. $E[\epsilon_{it}\epsilon_{is}] = 0$ for all $s \neq t$, is tested according to Wooldridge (2002). The null of no serial correlation cannot be rejected. A Breusch-Pagan/Cook Weisberg test is used to test on homoscedasticity, $E[\epsilon_{it}^2] = \sigma_\epsilon^2$. The test reveals the presence of heteroscedasticity in the error terms. We therefore conduct our analysis with heteroscedasticity-robust standard errors, see Stock and Watson (2008). An overidentification test using the Hansen Sargan statistic on fixed effects vs. random effects with robust standard errors rejects the null of independence of random effects and regressors and confirms the presence of fixed effects.

7 Conclusion

This paper contributes to the empirical literature on herding by using high-frequent investor-level data directly identifying the institutional transactions. The analysis therefore overcomes the data problems that previous studies face and provides new evidence on the short-term herding behavior of financial institutions.

Applying the measure of Lakonishok et al. (1992) for a broad cross section of German stocks over the period from August 2006 until April 2009, we find an overall level of herding of 1.44% for all investigated financial institutions which is quite low. By building more homogeneous subgroups of institutions, the level of herding rises substantially.

As opposed to findings in prior studies, our results do not confirm that small capital-

regression and all positive in the sell herding regression. However, coefficient estimates of returns prior to $t-2$ are insignificant. Moreover, instead of measuring daily $r_{i,t-1}$ with regard to the closing prices on day $t-1$ and $t-2$, we also use a weekly return measure, i.e. calculated from closing prices on $t-1$ and $t-6$. Our results in all regressions do not change qualitatively. For brevity, these results are not presented and are available on request.

ization stocks are more vulnerable to herding behavior. We find that herding is more pronounced in DAX 30 shares with a herding level of 3.63% for all institutions and 5.17% for the 30 most active institutions. These results suggest that herding behavior is not attributed to less information availability or information asymmetry but rather occurs unintentionally.

Our regression analysis confirms this conclusion and gives further insights on the determinants of herding. Herding depends on past volatility and past returns of the specific stock. Herding on the buy side is negatively related, whereas herding on the sell side is positively related to past returns. These results imply contrary to previous studies, that financial institutions are not engaged in positive feedback strategies.

Moreover, we found that financial institutions herd more on the sell side according to a rise in volatility of the stocks. This result is in line with the predictions of Persaud (2002) who argued that the common use of VaR models reduce the diversity of decision rules forcing banks to act like a herd. Regulators should therefore keep in mind the macro-prudential aspects of risks and incentive diversity of behavior among the market participants through the use of different risk management systems.

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A Appendix

Table 6: Statistics on Trading of Institutions

	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

Notes: 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.

Table 7: Mean Daily Herding Measures (2)

	MDAX			SDAX		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.24	1.33	1.16	−0.03	−0.04	−0.01
	(0.04)	(0.05)	(0.07)	(0.05)	(0.07)	(0.07)
Observations	33,616	17,395	16,219	29,325	14,808	14,515
<08/09/07	0.99	1.10	0.87	−0.59	−0.49	−0.68
	(0.05)	(0.08)	(0.08)	(0.07)	(0.10)	(0.10)
Observations	13,005	6,695	6,310	11,825	6,031	5,794
≥08/09/07	1.41	1.47	1.34	0.34	0.26	0.43
	(0.05)	(0.07)	(0.08)	(0.07)	(0.10)	(0.10)
Observations	20,611	10,700	9,909	17,500	8,777	8,721

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the MDAX and SDAX stocks considering all institutions in the sample. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Table 8: Daily Herding Measures of 30 Most Active Traders (2)

	MDAX			SDAX		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.18	1.39	0.96	1.59	1.86	1.28
	(0.05)	(0.07)	(0.07)	(0.09)	(0.12)	(0.14)
Observations	31,668	16,439	15,211	16,442	8,675	7,765
<08/09/07	1.78	2.67	0.65	1.85	2.39	1.14
	(0.07)	(0.11)	(0.10)	(0.12)	(0.16)	(0.20)
Observations	12,749	7,137	5,612	9,186	5,185	4,001
≥08/09/07	0.76	0.40	1.15	1.25	1.07	1.43
	(0.07)	(0.09)	(0.10)	(0.14)	(0.21)	(0.20)
Observations	18,919	9,302	9,599	7,256	3,490	3,764

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for MDAX and SDAX stocks considering only the 30 most active institutions in the sample. These 30 institutions are identified according to their overall trading volume over the whole sample period and all sample stocks. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Table 9: Daily Herding Measures of 40 Most Active German Banks (1)

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	2.16 (0.03)	2.11 (0.05)	2.31 (0.05)	5.21 (0.05)	5.05 (0.08)	5.30 (0.08)
Observations	69,274	34,573	34,694	20,897	10,132	10,764
<08/09/07	1.96 (0.05)	2.07 (0.04)	1.85 (0.08)	4.78 (0.08)	5.65 (0.09)	4.86 (0.12)
Observations	27,635	13,728	13,907	8,425	4,044	4,381
≥08/09/07	2.39 (0.04)	2.13 (0.07)	2.45 (0.07)	5.48 (0.04)	5.41 (0.12)	5.73 (0.10)
Observations	41,639	20,845	20,787	12,472	6,088	6,383

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering only the 40 largest German banks that are engaged in proprietary trading. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Table 10: Daily Herding Measures of 40 Most Active German Banks (2)

	MDAX			SDAX		
	HM	*BHM*	*SHM*	*HM*	*BHM*	*SHM*
Whole sample	1.22	1.29	1.15	0.22	0.11	0.34
	(0.05)	(0.07)	(0.07)	(0.08)	(0.12)	(0.12)
Observations	31,630	16,050	15,575	16,747	8,391	8,355
<08/09/07	1.25	1.40	1.10	0.14	0.31	0.63
	(0.07)	(0.11)	(0.10)	(0.12)	(0.18)	(0.17)
Observations	12,072	6,043	6,029	7,138	3,641	3,497
≥08/09/07	1.21	1.22	1.18	0.50	0.04	1.05
	(0.07)	(0.09)	(0.08)	(0.11)	(0.16)	(0.16)
Observations	19,558	10,007	9,546	9,609	4,750	4,858

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for MDAX and SDAX stocks considering only the 40 largest German banks that are engaged in proprietary trading. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Table 11: Mean Daily Herding Measures - Different Minimum Numbers of Trader Active (1)

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
>0 trader	1.55	1.54	1.56	3.65	3.43	3.84
	(0.02)	(0.04)	(0.02)	(0.04)	(0.06)	(0.06)
Observations	87,839	44,044	43,773	20,904	9,991	10,909
>5 trader	1.40	1.36	1.45	3.65	3.42	3.85
	(0.02)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
Observations	83,842	42,193	41,644	20,901	9,990	10,910
>10 trader	1.71	1.69	1.73	3.63	3.38	3.86
	(0.02)	(0.03)	(0.03)	(0.04)	(0.06)	(0.06)
Observations	69,474	35,035	34,426	20,900	9,965	10,931
>20 trader	2.57	2.56	2.57	3.62	3.42	3.80
	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
Observations	42,385	21,270	21,108	20,201	9,729	10,468

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and the sub-sample of DAX 30 stocks considering all institutions in the sample but 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.

Table 12: Mean Daily Herding Measures - Different Minimum Numbers of Trader Active (2)

	MDAX			SDAX		
	HM	*BHM*	*SHM*	*HM*	*BHM*	*SHM*
>0 trader	1.25	1.33	1.16	0.54	0.62	0.46
	(0.04)	(0.05)	(0.06)	(0.05)	(0.08)	(0.08)
Observations	33,673	17,455	16,209	33,262	16,598	16,655
>5 trader	1.24	1.33	1.16	−0.03	−0.04	−0.01
	(0.04)	(0.05)	(0.07)	(0.05)	(0.07)	(0.07)
Observations	33,616	17,395	16,219	29,325	14,808	14,515
>10 trader	1.30	1.41	1.19	0.06	0.25	−0.13
	(0.04)	(0.05)	(0.06)	(0.06)	(0.08)	(0.08)
Observations	31,864	16,451	15,408	16,710	8,619	8,087
>20 trader	1.74	1.95	1.53	0.77	1.23	0.20
	(0.04)	(0.07)	(0.07)	(0.10)	(0.17)	(0.17)
Observations	19,116	9,833	9,280	3,068	1,708	1,360

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for MDAX and SDAX stocks considering all institutions in the sample but 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.

Table 13: Mean Monthly Herding Measures (1)

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.97	1.67	2.27	3.03	2.76	3.30
	(0.07)	(0.13)	(0.13)	(0.16)	(0.23)	(0.23)
Observations	4,171	2,092	2,079	990	491	499
<08/07	1.36	1.35	1.38	3.00	3.18	2.85
	(0.12)	(0.18)	(0.16)	(0.22)	(0.35)	(0.28)
Observations	1,710	850	860	410	182	228
≥08/07	2.39	1.89	2.89	3.06	2.52	3.68
	(0.13)	(0.18)	(0.20)	(0.23)	(0.30)	(0.37)
Observations	2,461	1,242	1,219	580	309	271

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering all institutions in the sample. The measures are calculated considering a minimum number of 5 traders for each stock during each month. The herding measures are first computed over the whole sample stocks and over all months and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Table 14: Mean Monthly Herding Measures (2)

	MDAX			SDAX		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.98 (0.14)	1.95 (0.19)	2.02 (0.21)	1.29 (0.17)	0.62 (0.24)	1.87 (0.24)
Observations	1,597	862	735	1,584	739	845
$<$08/07	1.05 (0.18)	1.17 (0.26)	0.91 (0.25)	0.65 (0.22)	0.50 (0.34)	0.80 (0.30)
Observations	650	353	297	650	315	335
$\geq$08/07	2.62 (0.20)	2.50 (0.27)	2.77 (0.30)	1.73 (0.24)	0.71 (0.34)	2.58 (0.34)
Observations	947	509	438	934	424	510

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the MDAX and SDAX stocks considering all institutions in the sample. The measures are calculated considering a minimum number of 5 traders for each stock during each month. The herding measures are first computed over the whole sample stocks and over all months and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Table 15: Mean Quarterly Herding Measures (2)

	MDAX			SDAX		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	2.14 (0.23)	2.44 (0.30)	1.81 (0.35)	1.63 (0.27)	0.79 (0.36)	2.29 (0.31)
Observations	534	285	249	530	233	297
<3.Q./07	1.62 (0.32)	2.19 (0.44)	1.01 (0.46)	0.82 (0.35)	1.05 (0.55)	0.61 (0.43)
Observations	200	103	97	200	96	104
≥3.Q./07	2.46 (0.31)	2.58 (0.40)	2.32 (0.49)	2.12 (0.38)	0.60 (0.48)	3.20 (0.55)
Observations	334	182	152	330	137	193

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the MDAX and SDAX stocks considering all institutions in the sample. The measures are calculated considering a minimum number of 5 traders for each stock during each quarter. The herding measures are first computed over the whole sample stocks and over all quarters and than averaged across the different time spans and the sub-sample of stocks. Standard errors are given in parentheses.

Table 16: Mean Daily Herding Measures - Cutoff Size (2)

	MDAX			SDAX		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	5.27	5.22	5.31	3.90	3.61	4.19
	(0.04)	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)
Observations	32,438	16,180	16,258	26,709	13,349	13,360
<08/09/07	2.54	2.76	2.55	2.47	2.41	2.54
	(0.03)	(0.06)	(0.06)	(0.07)	(0.10)	(0.11)
Observations	12,857	6,656	6,201	11,468	6,073	5,395
≥08/09/07	5.99	6.94	7.02	4.97	4.61	5.30
	(0.04)	(0.09)	(0.09)	(0.08)	(0.12)	(0.12)
Observations	19,581	9,524	10,057	15,241	7,276	7,965

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the MDAX and SDAX stocks considering all institutions in the sample but dropping transactions below €14,000 for MDAX stocks and €7,000 for SDAX stocks. Standard errors are given in parentheses. The measures are calculated considering a minimum number of 5 traders for each stock on each trading day. The herding measures are first computed over the whole sample stocks and over all trading days and than averaged across the different time spans and the sub-sample of stocks.

Table 17: Fixed Effects Panel Regression - Herding of 40 Most Active German Banks

	HM_{it}	BHM_{it}	SHM_{it}
Impact of Regressors			
$Size_{i,t-1}$	0.0028^{*}	0.0058	0.0104^{***}
	(0.0016)	(0.0040)	(0.0032)
Vol_{it}	0.0122^{***}	0.0170^{***}	0.0083^{***}
	(0.0006)	(0.0018)	(0.0015)
$\|r_{i,t-1}\|$	0.0006^{**}		
	(0.0002)		
$r_{i,t-1}$		-0.0004^{**}	0.0003^{*}
		(0.0002)	(0.0001)
Std_{it}	0.0015^{**}	-0.0018	0.0022^{**}
	(0.0007)	(0.0012)	(0.0010)
Diagnostics			
$Wooldridge$	$F = 1.298$	$F = 3.382$	$F = 0.873$
	$(Prob{>}F{=}0.2568)$	$(Prob{>}F{=}0.0782)$	$(Prob{>}F{=}0.3518)$
$Cook - Weisberg$	$\chi^2 = 3869.82$	$\chi^2 = 1924.52$	$\chi^2 = 1617.43$
	$(Prob{>}\chi^2{=}0.0000)$	$(Prob{>}\chi^2{=}0.0000)$	$(Prob{>}\chi^2{=}0.0000)$
$Sargan - Hansen$	$\chi^2 = 18.188$	$\chi^2 = 27.207$	$\chi^2 = 15.107$
	$(Prob{>}\chi^2{=}0.0011)$	$(Prob{>}\chi^2{=}0.0000)$	$(Prob{>}\chi^2{=}0.0565)$
Observations	66,350	33,079	33,265

Notes: The herding measure HM_{it} for the subgroup of 40 largest German banks is regressed on variables $Size_{i,t-1}$, Vol_{it}, $|r_{i,t-1}|$ and Std_{it}. The buy and sell herding measures BHM_{it} and SHM_{it} is regressed on variables $Size_{i,t-1}$, Vol_{it}, $r_{i,t-1}$ and Std_{it}. The variable $Size_{i,t-1}$ is the logarithm of market capitalization, Vol_{it} is the logarithm of the trading volume of stock, $r_{i,t-1}$ is the daily stock return and $|r_{i,t-1}|$ is its absolute value. Std_{it} measures the standard deviation of past 250 daily stock returns. The statistical significance at 1%, 5% and 10% is represented as ***, **, and * respectively. Standard errors are given in parentheses in the upper part of the table. The lower part of the table reports test statistics and p-values in parentheses. $Wooldridge$ and $Cook - Weisberg$ are tests on serial correlation and heteroscedasticity of error terms. $Sargan - Hansen$ displays the overidentification test on the independence of random effects.

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