Herding of Institutional Traders: New Evidence from Daily Data

Stephanie Kremer

School of Business & Economics

Discussion Paper

Economics

2010/23

978-3-941240-35-3

Herding of Institutional Traders: New Evidence from Daily Data

Stephanie Kremer*

Free University Berlin

October 5, 2010

Abstract

This paper sheds new light on herding of institutional investors by using a unique database that identifies every transaction made by financial institutions in the German stock market. *First*, the analysis reveals that herding behavior of institutions occurs daily. *Second*, replication of the analysis with low-frequency and anonymous transaction data indicates that previous studies overestimate herding. *Third*, our results suggest that herding by large financial institutions mainly results from shared preference and investment styles. *Fourth*, a panel analysis shows that herding on the sell side in stocks is positively related to past returns and past volatility, whereas herding on the buy side is negatively related to these variables. Hence, large financial institutions do not demonstrate positive feedback strategies.

Keywords: Investor Behavior, Institutional Trading, Stock Prices

JEL classification: G11, G24, C23

*This research was supported by the Deutsche Forschungsgemeinschaft through the CRC 649 "Economic Risk". I thank Dieter Nautz for helpful comments, suggestions, and overall encouragement. I thank the German Federal Financial Supervisory Authority (Bundesanstalt für Finanzdienstleistungsaufsicht - BaFin) for providing data and, in particular, Michael Kollak for help with these data.
Free University Berlin, Germany, 14195 Berlin, Boltzmannstraße 20. E-mail: stephanie.kremer@fu-berlin.de

1 Introduction

A growing body of literature establishes the tendency of investors to accumulate on the same side of the market, known as herding behavior. This kind of trading pattern is often held responsible for destabilizing stock prices, increasing price volatility, and generally threatening the stability of the financial market (see, e.g., Scharfstein and Stein (1990), Hirshleifer and Teoh (2003), or Hwang and Salmon (2004)). There are several types of herd behavior, distinguished by various explanations for the co-movement. Generally, herding is dived into sentiment-driven *intentional herding* and *unintentional herding* driven by fundamentals (see, e.g., Bikhchandani and Sharma (2001)). Distinguishing between different sources of herding is crucial not only for regulatory purposes, but also in discovering whether herding leads to market inefficiency and/or 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 predominance of this class of investors in the stock market, institutions have the power to move the market and impact prices, even more if they herd. This possibility, and its consequences, emphasizes the importance of discovering *first* whether institutional investors herd and, if so, *second* the determinants of such behavior.

To date, the literature on institutional herding has been severely handicapped by the unavailability of appropriate data; however, this current paper employs a unique dataset comprised of daily-investor level data. Previous studies rely either on *low-frequency data* or on *anonymous transaction data*. Empirical assessment of herding requires disaggregated investor-level data. In general, the positions taken by institutions on the stock market are reported *infrequently*, if at all. For example, for U.S. mutual funds or other institutional investors, reports of holdings are available only on a quarterly basis (see, e.g., Choi and Sias (2009), Wermers (1999)). Using such low-frequency data does not allow capturing trades that are completed within the period and does not reveal herding if it occurs within a shorter time interval. Studies employing this type of data are also limited in the investigation of the determinants of herding. There is no resolution on intra-quarter covariances of trades and returns and thus, these studies fail to conclude whether institutions are *reacting* to or *causing* stock price movements, see Lakonishok, Shleifer and Vishny (1992).

A part of the empirical literature, e.g., Barber, Odean and Zhu (2009), attempts to overcome the problem of data frequency by using *anonymous transaction data* instead of reported holdings. However, those data do not identify the trader. Therefore, work on this front separates trades by size and then identifies trades above a specific cutoff size as institutional. However, even though 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 create sub-samples of traders. As a result, the sources of herding remain unclear.

The current paper makes two main contributions to the literature. *First*, by using a new dataset, that includes high-frequency investor-level data that directly identify institutional transactions, this paper overcomes the above-mentioned data limitations. The analysis provides new evidence on the herding behavior of financial institutions for a broad cross-section of stocks over the period from July 2006 to March 2009 in the German stock market.[1] By replicating the analysis with low-frequency data as well as with cutoff levels, we find that previous studies might overestimate the extend of herding. As a *second* contribution, and an improvement on previous descriptive approaches, daily data combined with a panel analysis allow investigation into possible sources of herding.

The estimation results reveal that financial institutions do indeed evidence herding behavior and that this herding depends on stock characteristics as well as on past returns and stock volatility. In particular, we find –contrary to previous evidence–

[1] The paper offers the first empirical investigation of herding by banks and other financial institutions in the German stock market. Walter and Weber (2006) has analyzed herding for German mutual funds at a semi-annual frequency.

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% according to the Lakonishok et al. (1992) herding measure. Moreover, herding on the sell side is positively related to past returns and past volatility whereas herding on the buy side is negatively related to these variables. These results can be explained by *unintentional* herding that results from shared investment styles and common risk models. These conclusions hold irrespective of the herding measure applied. Results obtained with the dynamic measure of Sias (2004) show 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 (i.e., *unintentional herding*).

The rest of the paper is structured as follows: Section 2 reviews the theory behind herding behavior. Section 3 summarizes the extend literature. Section 4 introduces the data. Section 5 discusses the herding measures. Section 6 presents the empirical analysis. Section 7 offers a summary of the main results and some 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 act like a "herd." There are several types of herd behavior, defined by various explanations for the co-movement. Generally, herding is divided into *intentional herding* and *unintentional*, or *spurious herding* (see, e.g., Bikhchandani and Sharma (2001)).

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, Subrahmanyam and Titman (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.

From a macroeconomic perspective, *unintentional* herding can be an efficient outcome if it is driven by fundamentals. In contrast, *intentional* herding is generally considered to be inefficient. Intentional herding is morse 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 destabilization of markets, thus having the potential to create, or at least 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 point of view, the impetus underlying imitation has often been assumed to stem from human nature itself, in the sense that people may tend toward conformity (Hirshleifer (2001)) as a result of their interactive communication. Yet, intentional herding might be rational from the trader's 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)) traders copy the investment activity of other market participants because they infer (from observed trading behavior) that others have relevant information, resulting in an informational cascade. This can occur when either the trader has no information himself when he beliefs his own information is uncertain and that others are better informed. The trader might ignore his information, even if this information is superior, because it is not strong enough to change the crowd behavior. However, under this model, herding mainly occurs in the short-term, since the arrival of public information and consequent 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 turnover in developed markets, information is usually timely incorporated into asset prices, thus rendering them more informative.

Reputation Based Model

Another explanation for herding behavior is posited by the *reputation based model* originally developed by Scharfstein and Stein (1990). According to this model, 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 pits them against each other. Thus, at least traders with poorer reputations have an incentive to imitate those with better reputations. Overall, traders might perceive the consequences of a potential failure as outweighing the benefits of a potential success from going it alone (Graham (1999)). Scharfstein and Stein (1990) call this effect "sharing the blame."

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. Therefore, all types of herding are linked to the uncertainty or availability of information.

2.2 Revealing the Type of Herding

Distinguishing between different sources of herding behavior is crucial for regulatory purposes and in determining whether herding leads to market inefficiency. However, empirical discrimination between the different types is difficult due to the large number of factors that may influence an investment decision and because the motives behind a trade are not discernable.

2.2.1 Size Effects

The empirical literature explores the determinants of herding via the link between herding and information by considering variables that proxy, e.g., information availability.

Lakonishok et al. (1992) and Wermers (1999) segregate stocks by size because *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 of *intentional herding.*

2.2.2 Correlation of Trades Over Time

According to Sias (2004), the correlation of trades over time can be used to investigate intentional herding. If this correlation does indeed result from copying other institutions rather than following own trading strategies, it would be an indication of *intentional herding* that arises due to imitation of others.

2.2.3 Feedback Trading

As *unintentional herding* arises due to simultaneous reactions to 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 traders react to price signals, following Froot, Scharfstein and Stein (1992) and Sias (2004), this would be interpreted as evidence of unintentional herding. Even though herding resulting from correlated positive feedback trading is considered to be informed herding according to the theory above, such herding might also have a destabilizing impact on financial markets. Short-term strategies based on past returns imply pro-cyclical behavior that aggravates downward or upward pressures in the market (see, e.g., De Long, Shleifer, Summers and Waldmann (1990)).

2.2.4 Risk Management Systems

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, all selling the same stocks at the same time in response to negative shocks. Although this kind of trading is considered to be *unintentional herding*, it leads to further slumps in prices. As institutions are increasingly using the same VaR models, a situation brought about by regulators requiring high and common standards, the tendency is convergence of market participants behavior. In short, the market-sensitive risk management systems reduce the diversity of decision rules.

3 Related Empirical Literature

3.1 First Evidence

One of the earliest works related to herding is that of Kraus and Stoll (1972), who analyze parallel trading on a monthly basis among institutional investors such as mutual funds and banks and conclude that institutions do not tend to trade in parallel with each other. Lakonishok et al. (1992) adapt the central idea and construct a herding measure that is now a standard in the empirical literature. Lakonishok et al. (1992) test for herd behavior within a quarterly time span using a sample of U.S. equity funds covering the period 1985 to 1989. They find only low values of herding for their overall sample.

An alternative measure used in the literature is that constructed by Sias (2004). This measure quantifies the degree to which institutions follow institutional trades of the prior period. Using quarterly institutional data from 1983 to 1997, Sias (2004) finds strong evidence of herding. A related recent study by Choi and Sias (2009) investigates institutional herding in industries using the Sias herding measure. The authors also report strong evidence of herding. Both herding measures will be employed in this paper and will be explained in Section 5.

3.2 Size and Performance of Stocks

Lakonishok et al. (1992) also constructed subsamples based on past performance and the size of the stocks. Although different past performances of stocks did not lead to significantly greater herding, they find evidence of herding being more intense among small companies compared to large stocks, which is consistent with the theory of *intentional herding*. 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 U.S. 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 finds a greater degree of herding than Lakonishok et al. (1992) for a comprehensive sample of U.S. mutual funds during 1975-1994. He also finds 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), but in a U.K. context. For U.K. mutual funds over the period from 1986 to 1993, he finds that funds herd out of stocks that have performed well in the past. Sias (2004) finds that herding is related to positive feedback trading; however, his results suggest that herding is mainly due to informational cascades, i.e., *intentional herding*, which is also underlined by higher herding in smaller stocks. In line with this literature, we will also consider the impact of past performance and size effects on herding.

3.3 Development of the Market

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 U.S.-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 U.S. and U.K. capital markets. There is also evidence for 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.[2]

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, Ergul, Holmes and Priestley (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 will account for the impact of market transparency by investigating herding in different market segments.

3.4 State of the Market

There is also evidence that herding behavior may depend on the state of the overall market. Choe et al. (1999) find, for the Korean stock market, higher herding levels before the Asian crisis of 1997 than during the crises. Similarly, using data from U.S. and South Korean stock markets, Hwang and Salmon (2004) find more evidence of herding during relatively quiet periods than during periods when the market is under stress. In contrast, the results of Bowe and Domuta (2004), based on data from the Jakarta Stock Exchange, indicate that herding by foreigners increased following the outbreak of the crisis. Therefore, in this paper, we separate our sample into crisis and non-crisis periods to account for different herding intensities.

[2] Significant herding is reported 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)).

4 Data and Sample

4.1 Data Problems of Previous Literature

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

4.1.1 Low Frequency

Most studies on this topic identify institutional transactions as changes in reported positions in a stock. However, positions are reported very infrequently, if at all. For example, most of these studies focus on mutual funds as institutions, but in the U.S., mutual funds generally report on only a quarterly basis. For German mutual funds, half-year reports are required.[3] Semi-annual and even quarterly data provide only a crude basis for inferring trades and this frequency is especially too low in a rapidly changing stock market environment. As a result, herding might be understated, since trades that are completed within the period are not captured. Moreover, theory predicts that intentional herding arises due to informational cascades. However, in markets with frequent public information flows and high turnover that lead to the timely incorporation of information, informational cascades are likely to occur only in the short-term, that is, before public information becomes available. Alternatively, herding might 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. For long time intervals, the concepts of parallel and imitative behavior are severely stretched, to a level that causes concern. The studies are further 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, fine-grained or otherwise, of intra-quarter covariances

[3] 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. One recent study by Puckett and Yan (2008) uses weekly data and thus partially overcomes the low frequency problem.

of trades and returns; thus these studies are unable to discover whether institutions are reacting to stock price movements or causing price movements, see Lakonishok et al. (1992).

4.1.2 Identification of Traders

The second set of studies in this field attempts to overcome the lack of data problem by using transaction data and making assumptions about the trader. This work uses a naive cutoff approach to identify institutional trades. Transactions above a specific cutoff size are considered as a 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 can 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 although institutions trade often during a day, such trades are not necessarily large.[4]

4.2 The Unique BaFin Datasource

The dataset employed in this paper avoids most of the problems that plague earlier work by including disaggregated high-frequency investor-level data. In fact, 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 organized 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

[4] Moreover, since trades below \$5,000 are regarded as retail trades according to Lee and Radhakrishna (2000), a large number of trades (i.e., those between $50,000 and$5,000) remain unclassified.

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. Direct identification of the trading financial institution also enables us to create subgroups of institutions in order to examine differences in their behavior. We exclude institutions trading exclusively for the purpose of market making. Of course, institutions engaging in proprietary business may additionally act as market makers in some cases and the records do not distinguish between those trades. However, it is expected that the proportion is small in highly liquid markets.

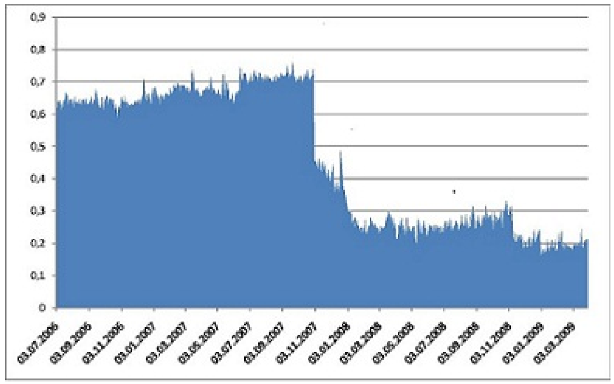
Using data from July 2006 until March 2009 (a total of 698 trading days), we cover market upturns as well as the recent market downturn. We will investigate whether trading behavior has changed due to market turmoil.

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 (a small-cap index of 50 stocks that rank behind the MDAX components).[5] These indices allow distinguishing between the trading behavior in small and large stocks.

Over the observation period, 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

[5] The stocks were selected according to the index compositions at the end of the observation period on March 31, 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, totaling 88,435 observations.

Figure 1: Share of Institutional Investors in the Trading Volume of DAX 30



Notes: The figure shows the development of the share that institutions have in the trading volume averaged over DAX 30 stocks. Source: BaFin records and Datastream.

recent financial crises, implying a retraction from trading business, see Figure 1. In the period from July 1, 2006 until August 8, 2007, the proportion constituted 66%, shrinking to 32% after August 9, 2007. Table 8 in the Appendix provides further information on the investigated institutions.

5 Do Institutions Herd?

5.1 The Herding Measures

5.1.1 The LSV Measure

In a first step, our analysis uses the herding measure 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 measure assumes that under the null hypothesis of no herding, the decision to buy or to sell is a bernoulli distributed random variable with equal success probability for all stocks at a given time.[6] Consider a number of N_{it} institutions trading in stock

[6]One implication of this assumption is that short selling must be possible. This assumption is not

i at time t. Out of these N_{it} transactions, a number of b_{it} are buy transactions. The buyer 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 at time t is determined by the overall probability to buy at time t for all stocks $\bar{br}_t$ and, additionally, by the degree of herding h_{it} in the specific stock i at time 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 at t corresponds to the overall probability to buy $(\bar{br}_t)$ at time t. The number of buys of stock i at 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 buyer ratio at t, $E_t[br_{it}] = \bar{br}_t$, i.e., the period average of the buyer ratio and thus the number of net buyers at time t aggregated across all stocks i divided by the number of all traders at time 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 at time t, i.e., as excess dispersion of what would be expected for that time. Therefore, the measure captures similar trading patterns beyond market trends and eliminates the influence of market-wide herding.

The LSV herding statistic is given by

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

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 engage in short sales. Thus, if they have no holding in stock i, they can act only as buyer and the action would not be binomially distributed.

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

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

Subtracting this term accounts for the possibility to observe more variation in the buyers ratio in stocks with only a 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 occurs the absolute value of $|br_{it} - \bar{br}_t|$ is likely to be greater than zero. Making this adjustment ensures that the herding measure HM_{it} will be zero if the trades are independent.[7]

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 $\overline{HM}$ 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 $\overline{HM}$ 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 analyzed.

[7] Following previous studies, e.g., Wermers (1999), HM_{it} is computed only if at least five traders are active in i at time t, leading to a loss of observations and an unbalanced panel. However, Table 8 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. Tables 13 and 14 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.

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 distinguish between "buy herding" BHM_{it} and "sell herding" SHM_{it}, to discover whether institutions buy or sell a stock i in herds. The sample is therefore separated into $BHM_{it} = HM_{it}$ 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 by SHM_{it} because in this case no herding occurs, i.e., there is no herding on either the buy or on the sell side.[8]

The discrimination between BHM_{it} and SHM_{it} captures asymmetries in institutions' behavior when buying or selling. The separate measurement of herding *into* stocks and *out* of stocks will be important when analyzing the determinants of trading behavior in Section 6.2.

5.1.2 The Sias Measure

The LSV herding measure is a static measure that detects contemporaneous buying or selling within the same time period. In contrast, Sias's (2004) dynamic approach explores whether the buying tendency of traders persists over time, directly testing whether institutional investors follow each others' trades by examining the correlation between institutional trades in one period and the next period. We will use this measure in Section 6.2 to arrive at deeper insight into the sources of herding and to better distinguish between *intentional* and *unintentional herding.*

The starting point of this measure is again the number of buyers as a fraction of all traders. For the sake of comparison, we refer to the same denomination as in the previous section, i.e., the buyer ratio br_{it}. According to Sias (2004), the ratio is standardized to have zero mean and unit variance:

$$\Delta_{it} = \frac{br_{it} - \bar{br}_t}{\sigma(br_{it})}, \tag{5}$$

where $\sigma(br_{it})$ is the standard deviation across stocks at time t.

[8] Comparing the observations in, e.g., Table 6, the resulting loss of data is not empirically relevant.

The Sias herding measure is defined as the correlation between the standardized buyer ratios in consecutive periods:

$$\Delta_{it} = \beta_t \Delta_{i,t-1} + \epsilon_{it}. \tag{6}$$

The cross-sectional regression is estimated for each day t and then the time-series average of the coefficients is calculated: $\beta = \frac{\sum_{t+1}^{T} \beta_t}{T-1}$. A positive and significant coefficient β can be interpreted as first evidence of herding.[9]

Thus, 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. Alternatively, a buyer ratio of 51% would lead to moderate herding as determined by the LSV measure, but could show strong evidence of herding according to Sias, if this low ratio persists in the next period.

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

$$\begin{aligned}\beta = \rho(\Delta_{it}, \Delta_{i,t-1}) = &\left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \frac{(D_{nit} - \bar{br}_t)(D_{ni,t-1} - \bar{br}_{t-1})}{N_{it} N_{i,t-1}}\right] \\ &+ \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \sum_{m=1, m \neq n}^{N_{i,t-1}} \frac{(D_{nit} - \bar{br}_t)(D_{mi,t-1} - \bar{br}_{t-1})}{N_{it} N_{i,t-1}}\right],\end{aligned} \tag{7}$$

where N_{it} is again the number of institutions trading stock i during day t. I is the number of stocks traded by the institutions at time t. D_{nit} is a dummy variable that equals one if institution n is a buyer in i at time t; zero otherwise. Also, $D_{mi,t-1}$ is a dummy variable that equals one if trader m (who is different from trader n) is a buyer at day $t-1$.

[9] As in the case of the LSV measure and in line with Sias (2004) only observations with at least five traders active in i at time t are considered in the estimation.

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 Choi and Sias (2009), Equation (7) can be further decomposed to distinguish between the correlations associated with "buy herding" and "sell herding". Hence, stocks are classified by whether institutions bought in $t-1$ ($br_{i,t-1} > 0.5$) or sold in $t-1$ ($br_{i,t-1} < 0.5$).

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 evidence for informational cascades, i.e., *intentional herding*.[10]

5.2 Results on LSV Herding

5.2.1 Daily Herding Measure for All Institutions

Our results regarding overall LSV 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 found in previous studies using low-frequency data, e.g., Lakonishok et al. (1992) and Walter and Weber (2006), both of which found herding to be about 2.70%.

Table 1 shows a significantly higher herding measure in DAX 30 stocks: the mean herding measure for stocks in this major German index is 3.63%, i.e., about 2.5 times larger than for the whole sample. Therefore, in contrast to previous findings (e.g., Wermers (1999) or Lakonishok et al. (1992)), reporting that correlated trading is higher in small stocks, our sample institutions particularly herd in to and out of large stocks.

[10]This part of the correlation will be insignificant if institutional trades are independent of other institutional trades on the previous day. A negative correlation would indicate that institutions act in the opposite direction than did the others on the day before.

Table 1: Mean Daily LSV Herding Measures (1)

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	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
<08/09/07	1.32	1.29	1.27	4.35	4.23	4.46
	(0.04)	(0.05)	(0.05)	(0.06)	(0.09)	(0.08)
Observations	33,257	16,832	16,425	8,427	4,106	4,321
≥08/09/07	1.60	1.38	1.58	3.17	2.86	3.45
	(0.03)	(0.05)	(0.05)	(0.06)	(0.08)	(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.

Table 9 in the Appendix shows that daily herding measures for MDAX stocks are significantly lower (1.24%) and daily herding in SDAX is actually insignificant. This result is also in contradiction of the theory of *intentional herding*, which predicts higher herding levels in stocks with less information availability and asymmetry. The herding behavior is thus more likely of the *unintentional* type.

We also consider different periods for computing the average herding measure to investigate whether herding varies between the crisis and non-crisis period, i.e., before and after August 9, 2007. Results displayed in Table 1 reveal slightly more evidence of herding in DAX 30 stocks before the financial crises but herding over all stocks and MDAX and SDAX stocks is higher during the crises. 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 during the financial crisis but could also be related to lower or negative returns on the stocks, suggesting positive feedback trading. Empirical analysis discussed in Section 6.2 sheds light on this issue.

5.2.2 The Role of Low-Frequency and Cutoff Size

The bulk of the literature on herding by necessity relies either on lower frequency data or uses transaction data and makes assumptions regarding the identity of the trader using a cutoff approach for identifying institutional trades. For the sake of comparison and to shed more light on 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.

Simulation with Low-Frequency

Table 2: Mean Quarterly LSV 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 a 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.

For this analysis, instead of using the daily trade imbalance of a specific institution, we calculate monthly and quarterly trade imbalances. Results displayed in Table 2 reveal that herding measures are higher on a quarterly horizon and in a range similar to that found in previous studies using quarterly data. Comparing daily, monthly, and quarterly results (see also Tables 15 - 17 in the Appendix), the herding measure rises when lower frequency data are employed, indicating a slight overestimation of herding measures, particularly for small-capitalized stocks, when using low-frequency data.

Simulation with Cutoff Size

Table 3: Mean Daily LSV 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. See Table 1 for further information.

Following studies that use cutoff approaches to identify institutional transactions (e.g., Barber et al. (2009)), we drop from our sample institutional trades below a specific size. 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. We ignore trader identification, thus treating every remaining transaction independently, i.e., if the same institution trades more than once during a day, its transactions are regarded as trades by different institutions.

The results for the mean daily herding measures are displayed in Table 3 and for MDAX and SDAX stocks in Table 18 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 extend of herding.

5.2.3 Subgroups of Institutions

The theory of *unintentional herding* predicts higher herding levels among institutions that 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 who are evaluated against each other (see Scharfstein and Stein (1990)). The overall sample investigated in Section 5.2.1 is comprised of a large heterogeneous group of institutions, but the herding behavior of subgroups of institutions is of interest as well, and we now shift our focus to these groups.

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

Creating a subsample based on the trading activity reveals a higher herding measure for the 30 most active traders, see Table 4.[11] The mean daily herding measure across all stocks is 2.5%. 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 during the financial crisis but could also be related to lower or negative returns of the stocks, suggesting positive feedback trading. Our empirical analysis in Section 6.2 shall provides more insight into this issue.

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

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	2.48 (0.03)	2.67 (0.05)	2.30 (0.05)	5.18 (0.06)	5.28 (0.08)	5.08 (0.08)
Observations	68,963	35,806	33,130	20,853	10,692	10,154
<08/09/07	2.93 (0.05)	3.55 (0.07)	2.15 (0.08)	5.84 (0.08)	6.26 (0.12)	5.35 (0.12)
Observations	30,362	16,868	13,494	8,427	4546	3,881
≥08/09/07	2.14 (0.05)	1.87 (0.07)	2.41 (0.07)	4.73 (0.08)	4.55 (0.12)	4.92 (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. See Table 1 for further information.

Considering DAX 30 stocks, the herding measure rises to 5.17%, a high level of herding compared to previous findings. For MDAX and SDAX stocks, the herding measure is also higher, but still small, see Table 10 in the Appendix.

The subgroup of the 30 most active traders includes a few financial institutions other than banks (i.e. financial service institutions) and also several foreign investment banks.

[11] 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.

We create another subsample comprising only the 40 most active German banks that are engaged in proprietary trading on stock markets.[12] These banks are all subject to the same regulatory regime and oversight by the financial authority. Although the regulatory framework and risk management systems for the foreign banks are expected to be similar, for these German banks we were able to ensure –by means of 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 11 in the Appendix are similar to those 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, whereas sell herding is more pronounced during the crisis. Results for MDAX and SDAX stocks are again significantly lower and even insignificant in case of buy herding in SDAX stocks, see Table 12 in the Appendix.

6 Revealing the Determinants of Herding

6.1 Possible Determinants of Herding

According to the theory discussed in Section 2.1 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. In our investigation of the sources of herding, we thus focus especially on empirical proxies to measure information availability, information asymmetry or uncertainty in the market and on those determinants that may imply a destabilizing pro-cyclicality.

[12]We select those institutions according to their trading volume over the observation period in the selected stocks. We select only German institutions based on the definition of same in 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 is now comprised of 69,257 observations.

First, following previous literature on herding, we consider firm size ($Size$) as one possible determinant of herding. Small firms 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, the evidence reviewed in Section 3 finds a higher herding level in smaller stocks. In contrast, our results in Section 5.2 indicate higher herding in larger stocks. Firm size is measured by the logarithm of the previous day's closing market capitalization of the specific stock.

A *second* factor possibly related to herding could 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. Suominen's (2001) model suggests that higher trading volume indicates better information quality. Leuz and Verrecchia (2000) and Welker (2006) argue that market liquidity can be measured by transaction volumes or bid-ask spreads. We therefore use market volumes of stocks as a proxy for information asymmetry and expect, based on 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 the past 250 daily stock returns.[13] On the one hand, stock return volatility is assumed to reflect the extent of disagreement among market participants, thus proxying the degree of uncertainty in the market. Intentional herding models would therefore predict a 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 employed for risk management purposes and regulatory requirements, see Persaud (2002). The minimum observation period according to Basel II market risk standards is one year, i.e., 250 trading days. Therefore, in our subsample of the 30 most active traders, we expect to see more sell herding in stocks with higher past year standard deviation of stock

[13] We also use the last 90 and 30 stock returns to check robustness.

returns, since those regulated institutions highly engaged in trading generally use such risk management models. Moreover, our subgroup of 40 German banks is comprised exclusively of banks using VaR models and implementing regulatory or internal VaR limits.[14] A positive impact of volatility on sell herding but not on buy herding could then be considered as evidence of unintentional herding.

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

Table 5 summarizes the theoretical predictions on the determinants of herding. Note that the role of stock return volatility, Std, may differ for buy and sell herding.

Table 5: Theoretical Predictions on the Determinants of Herding

	Intentional	Unintentional
$Size$	$-$	$+$
Vol	$-$	$+$
r	0	$+/-$
Std^{*}	$+$	$-$

Notes: This table classifies the predicted impact of firm size ($Size$), trading volume (Vol), stock returns (r) and volatility (Std) on the herding measure. *In case of Std the classification may differ for buy and sell herding. "-", "+" and "0" denotes a negative, positive and insignificant impact, respectively.

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

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:

$$HM_{it} = a + bSize_{i,t-1} + cVol_{it} + d|r_{i,t-1}| + eStd_{it} + \alpha_i + \gamma_t + \epsilon_{it}, \tag{8}$$

where HM_{it} is the LSV herding measure as calculated according to Equation (3). $Size_{i,t-1}$ is measured by the logarithm of the previous day's closing market capitalization of stock i. Vol_{it} captures the logarithm of the trading volume of stock i during trading day t. $|r_{i,t-1}|$ 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 sell sides. Std_{it} is the volatility, measured as the standard deviation of the past 250 daily stock returns. α_i are heterogenous stock-specific effects and γ_t are time dummies.[15]

We concentrate on the herding measures for the two homogeneous subgroups of the 30 most active traders and the 40 most active German banks. We are especially interested in whether their higher herding measures result from *unintentional herding* due to a shared investment style or from *intentional herding* due their membership in the same peer group, see Section 2.1. Moreover, these institutions are the most relevant for the stock market. The discovery of intentional herding or pro-cyclical behavior by these groups would suggest a high potential threat to for financial stability.

Table 6 shows the results of a fixed effects panel regression with the 30 most active traders. Results for the 40 largest German banks are again similar and are displayed in Table 19 in the Appendix. Let us first look at the results for the regression with the unsigned herding measure HM, which are displayed in the first column. The

[15] 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.

Table 6: 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	0.0029	0.0016
	(0.0027)	(0.0020)	(0.0019)
Vol_{it}	0.0069^{***}	0.0023^{***}	0.0082^{***}
	(0.0012)	(0.0007)	(0.0008)
$\|r_{i,t-1}\|$	-0.0001		
	(0.0003)		
$r_{i,t-1}$		-0.0015^{***}	0.0008^{***}
		(0.0002)	(0.0002)
Std_{it}	0.0031^{***}	-0.0096^{***}	0.0020^{***}
	(0.0012)	(0.0009)	(0.0012)
$Dummy^b_{i,t}$		0.0156^{***}	
		(0.0011)	
$Dummy^s_{i,t}$			0.0111^{***}
			(0.0002)
Diagnostics			
$Wooldridge$	$F = 0.346$	$F = 0.251$	$F = 0.666$
	($Prob$>F=0.5573)	($Prob$>F=0.6170)	($Prob$>F=0.4159)
$Cook - Weisberg$	$\chi^2 = 3383.14$	$\chi^2 = 4924.52$	$\chi^2 = 1290.95$
	($Prob$>χ^2=0.0000)	($Prob$>χ^2=0.0000)	($Prob$>χ^2=0.0000)
$Sargan - Hansen$	$\chi^2 = 10.343$	$\chi^2 = 16.422$	$\chi^2 = 17.536$
	($Prob$>χ^2=0.0350)	($Prob$>χ^2=0.0353)	($Prob$>χ^2=0.0036)
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. $Dummy^b_{it}$ ($Dummy^s_{it}$) is a dummy variable, that equals one, if buy herding (sell herding) occurred also on the previous day $t-1$, and zero otherwise. 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.

coefficient estimate for $Size$ is insignificant and the coefficient Vol is positive and statistically significant. First, this suggests that the evidence of higher herding levels for DAX 30 stocks in Section 5.2 is more likely the result of these stocks' higher liquidity than due to higher market capitalization. However, the size effect might already be captured by the fixed effects in the regression, since market capitalization changes only slightly over time.[16] 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 these large financial institutions are less likely to engage in *intentional herding*. The result could be an indication of *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 the 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 appears inconsistent since it hints at the existence of *intentional herding*. However, the estimate could also be related to the common use of risk management models that recommend selling the more volatile stocks. Results on buy and sell herding discussed below 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 differently. We therefore estimate Equation (8) separately for herding on the buy and sell side using the same set of explanatory variables, except that the absolute return $|r|$ is replaced by the signed return r as the direction of the recent price movement will affect whether momentum investors herd more on the buy or sell side:

[16] In a pooled OLS regression, market capitalization has a positive significant impact. Results are available on request.

$$BHM_{it} = a^b + b^b Size_{i,t-1} + c^b Vol_{it} + d^b r_{i,t-1} + e^b Std_{it} + e^b Dummy^b_{it} + \alpha^b_i + \gamma^b_t + \epsilon^b_{it} \quad (9)$$

$$SHM_{it} = a^s + b^s Size_{i,t-1} + c^s Vol_{it} + d^s r_{i,t-1} + e^s Std_{it} + e^s Dummy^s_{it} + \alpha^s_i + \gamma^s_t + \epsilon^s_{it} \quad (10)$$

In these regressions we also include a dummy variable $Dummy^b_{it}$ ($Dummy^s_{it}$), equal to one, if buy herding (sell herding) also occurred on the previous day $t-1$; zero otherwise. These dummies partly account for persistence of herding on either the buy or sell side.[17]

The results for the fixed effects regressions on buy and sell herding are reported in the second and third columns of Table 6. Estimates for Vol reveal that herding on the buy and sell sides is positively related to the liquidity of stocks. Again, market capitalization, measured as $Size$, does not play an important role.

The positive and significant impact of the dummy variables shows that herding on the buy side (sell side) is positively correlated with previous day's buy herding (sell herding). We shed more light on this correlation in the next section by using the Sias measure.

The results for r and Std are interesting. First, the coefficient estimate for Std on buy herding is significantly negative. In the case of sell-side herding Std, has a significant positive impact. Hence, the higher the volatility of a stock, the more herding occurs on the sell side. It is therefore unlikely that there is *intentional herding* behavior based on uncertainty in the market, since this should affect buy and sell herding in the same way. Apparently, institutions share the preference to sell (buy) stocks that have shown a high (low) volatility. This is a clear indication for *unintentional herding* that might be a result of risk management practices, see Persaud (2002).[18]

[17] We include dummy variables rather than the lagged endogenous variable to avoid too many missing observations. For a deeper look at the dynamics of herding, we employ the Sias measure in the next section. Note also that the exclusion of those dummies would not change the significance or the signs of the other covariates. The magnitude of the coefficients for r_{it} would increase slightly.

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

The estimated impact of returns r is statistically significant for buy and sell herding regressions. As in the 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 conclusion drawn in previous studies (e.g., Grinblatt et al. (1995), Wermers (1999) or Walter and Weber (2006)) that institutions are momentum investors and follow positive feedback strategies. In contrast, in our sample, institutions share a preference for buying past losers and selling past winners. Overall, the results indicate that herding occurs mostly *unintentionally* and is due to shared preferences and investment styles.[19]

The lower part of Table 6 presents the relevant test statistics and p-values of diagnostic tests. The three models (Equations 8) - (10) were estimated as fixed effects panel regressions using the within estimator, i.e., the Ordinary Least Squares (OLS) of deviations from stock-specific means, which is feasible according to the tests employed.[20] We account for heteroscedasticity in the error terms, by using heteroscedasticity-robust standard errors, see Stock and Watson (2008).

6.2.3 The Dynamics of Herding

Table 6 shows that the buy and sell herding measures are positively related to buy or sell herding on the previous day. To discover the reason behind this correlation and how the correlation affects our interpretation of the sources of herding, we use the methodology of Sias (2004), which explores whether the buying tendency of traders persists over time (see Section 5.1.2). One motivation for adopting this approach is to better distinguish between intentional and unintentional herding. To this end, the

[19]We also included lagged returns up to five 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 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, but are available on request.

[20]This estimator is feasible, since according to a Hausman test on endogeneity of the regressors, the null hypothesis of exogeneity cannot be rejected.

Sias measure directly indicates whether institutional investors follow each others' trades by examining the correlation between institutional trades in one period and the next period.

Table 7: Mean Sias Measure of 30 Most Active Traders

	Average Correlation	Partitioned Correlation	
		Follow own trades	Follow trades of others
Whole sample	16.42 (0.34)	11.40 (0.27)	5.02 (0.26)
<08/09/07	19.61 (0.57)	12.01 (0.40)	7.60 (0.24)
≥08/09/07	14.25 (0.52)	10.98 (0.38)	3.27 (0.23)
Buy Herding			
Whole sample	6.23 (0.23)	4.35 (0.14)	1.88 (0.15)
<08/09/07	7.65 (0.37)	4.74 (0.23)	2.91 (0.15)
≥08/09/07	5.27 (0.35)	4.09 (0.19)	1.18 (0.15)
Sell Herding			
Whole sample	10.19 (0.24)	7.06 (0.20)	3.13 (0.12)
<08/09/07	11.96 (0.33)	7.26 (0.29)	4, 70 (0.12)
≥08/09/07	8.98 (0.35)	6.90 (0.28)	2.08 (0.13)

Notes: This Table reports results of the Sias measure for all stocks in the samples but considering only the 30 most active institutions. The upper part of the table reports values of the average correlation in percentage terms of the coefficient β. The correlations where first estimated with a cross-sectional regression for each day t and stocks i. The reported correlations display the time-series average of the regression coefficients in percentage terms. The second and third column report the partitioned correlations that result from institutions following their own trades and institutions follow the trades of others, see Equation (7). In the lower parts of the table the correlation is partitioned into those stocks institutions purchased at the previous day (buy herding) and those institutions sold (sell herding). Standard errors are given in parentheses.

Table 7 displays the results obtained from the Sias herding measure for the 30 most active institutional traders. The estimated correlation at daily frequency over the complete period and over all stocks in the datasample is 16.42% (coefficient $\beta = 0.1642$), which is slightly higher than the value obtained by Sias (2004), but lower than the result of Puckett and Yan (2008) for weekly frequency.[21]

After decomposition of the coefficient into the two different sources of the correlation, results reveal that the institutions follow their own strategies as well as those of others (i.e., herd) in to and out of stocks. However, the greatest part of the correlation, about 69.42% (=0.1045/0.1642), results from institutions that follow their own trading strategies. A correlation of only 5.02% is found for institutions following the trades of others. In contrast, Sias (2004), Choi and Sias (2009), and Puckett and Yan (2008) find a higher proportion of following others at lower frequencies.[22]

Differentiating across the non-crisis and crisis period reveals higher correlation before the crisis. Also, differentiating between buy and sell herding, shows consistent with the LSV results, higher herding tendency on the sell side.

Overall, the results obtained from the Sias (2004) measure reveal a correlation of institutional buyer ratios. The results show that a main part of this correlation stems from institutions that follow their own trades (i.e., *unintentional herding*), while the evidence for institutions following others is less pronounced. This result suggests, that institutions are actually following their own trading strategies rather than herding *intentionally* as a result of informational cascades.

7 Conclusion

This paper contributes to the empirical literature on herding by using high-frequency investor-level data that directly identifies institutional transactions. The analysis there-

[21] Note that the inclusion of the control variables described earlier in the regression reduces the magnitude of the correlation (β) to 15.1%. However, the correlation is still significant.

[22] Results obtained for the 50 most active German banks are again similar and are displayed in Table 20 in the Appendix.

fore overcomes the data problems faced by previous studies and provides new evidence on the short-term herding behavior of financial institutions.

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 quite low. By creating 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 capitalization 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 the result of insufficient information availability or information asymmetry, but is rather unintentional.

Our regression analysis confirms this conclusion and provides further insight into 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.

We also find a correlation of buy herding or sell herding over time. Using the dynamic methodology of Sias (2004), results show that trades of institutions are correlated over time, but the main proportion stems from institutions following their own trading strategies. This again implies that although there may be some *intentional* herding, the main part of the correlated trades occur *unintentionally.*

Finally, we find that rising stock volatility leads to more sell-side herding by financial institutions. This result is in line with the predictions of Persaud (2002) who argues that the common use of VaR models reduces the diversity of decision rules, resulting in herding behavior by banks. Therefore, regulators need to be aware of how risk management systems, particularly those systems that used in common by a great many large institutions, can affect the macro-prudential aspects of risks and incentive diversity of behavior among market participants.

References

Antoniou, A., Ergul, N., Holmes, P. and Priestley, R. (1997). Technical Analysis, Trading Volume and Market Efficiency: Evidence from an Emerging Market, *Applied Financial Economics* **7**: 361–365.

Avery, C. and Zemsky, P. (1998). Multidimensional Uncertainty and Herd Behavior in Financial Markets, *American Economic Review* **88**: 724–748.

Banerjee, A. (1992). A Simple Model of Herd Behavior, *Quarterly Journal of Economics* **107**: 797–818.

Barber, B. M., Odean, T. and Zhu, N. (2009). Do Retail Trades Move Markets?, *Review of Financial Studies* **22**(1): 151–186.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992). A Theory of Fads, Fashion, Custom and Cultural Change as Informational Cascades, *Journal of Political Economy* **100**: 992–1026.

Bikhchandani, S. and Sharma, S. (2001). Herd Behaviour in Financial Markets, *IMF Staff Papers* **47**(3): 279–310.

Bowe, M. and Domuta, D. (2004). Investor Herding during Financial Crisis: A Clinical Study of the Jakarta Stock Exchange, *Pacific-Basin Finance Journal* **12**: 387–418.

Choe, H., Kho, B. and Stulz, R. (1999). Do Foreign Investors Destabilize Stock Markets? The Korean Experience in 1997, *Journal of Financial Economics* **54**: 227–264.

Choi, N. and Sias, R. W. (2009). Institutional Industry Herding, *Journal of Financial Economics* **94**: 469–491.

De Long, J. B., Shleifer, A., Summers, L. H. and Waldmann, R. J. (1990). Positive Feedback Investment Strategies and Destabilising Rational Speculation, *Journal of Finance* **45**: 379–395.

Diamond, D. W. and Verrecchia, R. E. (1991). Disclosure, Liquidity, and the Cost of Capital, *Journal of Finance* **46**(4): 1325–1359.

Froot, K., Scharfstein, D. and Stein, J. (1992). Herd on the Street: Informational Inefficiencies in a Market with Short-Term Speculation, *Journal of Finance* **47**: 1461–1484.

Gelos, G. and Wei, S.-J. (2002). Transparency and International Investor Behavior, *NBER Working Paper* **9260**.

Gilmour, S. and Smit, E. (2002). Institutional Herding: Evidence from the South African Unit Trust Industry, *Investment Analysts Journal* **55**: 14–26.

Graham, J. (1999). Herding Among Investment Newsletters: Theory and Evidence, *Journal of Finance* **1**: 237–268.

Grinblatt, M., Titman, S. and Wermers, R. (1995). Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior, *American Economic Review* **85**: 1088–1105.

Hirshleifer, D. (2001). Investor Psychology and Asset Pricing, *Journal of Finance* **56**(4): 1533–1598.

Hirshleifer, D., Subrahmanyam, A. and Titman, S. (1994). Security Analysis and Trading Patterns when Some Investors Receive Information Before Others, *Journal of Finance* **49**: 1665–1698.

Hirshleifer, D. and Teoh, S. (2003). Herd Behaviour and Cascading in Capital Markets: A Review and Synthesis, *European Financial Management* **9**: 25–66.

Hwang, S. and Salmon, M. (2004). Market Stress and Herding, *Journal of Empirical Finance* **11**: 585– 616.

Kallinterakis, V. and Kratunova, T. (2007). Does Thin Trading Impact upon the Measurement of Herding? Evidence from Bulgaria, *Ekonomia* **10**(1): 42–65.

Kim, K. A. and Nofsinger, J. R. (2005). Institutional Herding, Business Groups, and Economic Regimes: Evidence from Japan, *Journal of Business* **78**: 213–242.

Kim, W. and Wei, S.-J. (2002). Offshore Investment Funds: Monsters in Emerging Markets?, *Journal of Development Economics* **68**(1): 205–224.

Kraus, A. and Stoll, H. R. (1972). Parallel Trading by Institutional Investors, *Journal of Financial and Quantitative Analysis* **7**(5): 2107–2138.

Lakonishok, J., Shleifer, A. and Vishny, R. (1992). The Impact of Institutional Trading on Stock Prices, *Journal of Financial Economics* **32**: 23–43.

Lee, C. M. and Radhakrishna, B. (2000). Inferring Investor Behavior: Evidence from TORQ Data, *Journal of Financial Markets* **3**: 83–111.

Leuz, C. and Verrecchia, R. (2000). The Economic Consequences of Increased Disclosure, *Journal of Accounting Research* **38**: 91–124.

Lobao, J. and Serra, A. (2007). Herding behaviour: Evidence from portuguese mutual funds, *in* G. N. Gregoriou (ed.), *Diversification and Portfolio Management of Mutual Funds*, Palgrave MacMillan, New York, pp. 167–197.

Morris, S. and Shin, H. S. (1999). Risk Management with Interdependent Choice, *Oxford Review of Economic Policy* **15**(3): 52–62.

Oehler, A. and Wendt, S. (2009). Herding Behavior of Mutual Fund Managers in Germany, *Working Paper University of Bamberg* .

Persaud, A. (2000). Sending the Herd Off the Cliff Edge: The Disturbing Interaction Between Herding and Market-Sensitive Risk Management Practices, *Jacques de Larosiere Essays on Global Finance* (Washington: Institute of International Finance).

Persaud, A. (2002). Liquidity Black Holes, *Discussion Paper, United Nations University, World Institute for Development Economics Research* **31**.

Puckett, A. and Yan, X. S. (2008). Short-Term Institutional Herding and Its Impact on Stock Prices, *Working Paper, University of Missouri - Columbia* .

Scharfstein, D. and Stein, J. (1990). Herd Behavior and Investment, *American Economic Review* **80**: 465–479.

Shiller, R. J. (1990). Investor Behavior in the October 1987 Stock Market Crash: Survey Evidence, *Market Volatility* (Cambridge, Massachusetts: MIT Press).

Sias, R. (2004). Institutional Herding, *Review of Financial Studies* **17**: 165–206.

Stock, J. H. and Watson, M. W. (2008). Heteroskedasticity-Robust Standard Errors for Fixed Effects Panel Data Regression, *Econometrica* **76**(1): 155–174.

Suominen, M. (2001). Trading Volume and Information Revelation in the Stock Market, *Journal of Financial and Quantitative Analysis* **36**: 545–566.

Voronkova, S. and Bohl, M. (2005). Institutional Traders Behaviour in an Emerging Stock Market: Empirical Evidence on Polish Pension Fund Investors, *Journal of Business, Finance and Accounting* **32**(7): 1537–1560.

Walter, A. and Weber, F. (2006). Herding in the German Mutual Fund Industry, *European Financial Management* **12**(3): 375–406.

Welker, M. (2006). Disclosure Policy, Information Asymmetry and Liquidity in Equity Markets, *Contemporary Accounting Research* **11**: 801–827.

Wermers, R. (1999). Mutual Fund Herding and the Impact on Stock Prices, *Journal of Finance* **54**: 581–682.

Wylie, S. (2005). Fund Manager Herding: A Test of the Accuracy of Empirical Results Using U.K. Data, *Journal of Business* **78**(1): 381–403.

A Appendix

Table 8: 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
$\geq$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
$\geq$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 9: Mean Daily LSV 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. See Table 1 for further information.

Table 10: Daily LSV 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. See Table 1 for further information.

Table 11: Daily LSV Herding Measures of 40 Most Active German Banks (1)

	All Stocks			DAX 30		
	HM	*BHM*	*SHM*	*HM*	*BHM*	*SHM*
Whole sample	2.16	2.11	2.31	5.21	5.05	5.30
	(0.03)	(0.05)	(0.05)	(0.05)	(0.08)	(0.08)
Observations	69,274	34,573	34,694	20,897	10,132	10,764
<08/09/07	1.96	2.07	1.85	4.78	5.65	4.86
	(0.05)	(0.04)	(0.08)	(0.08)	(0.09)	(0.12)
Observations	27,635	13,728	13,907	8,425	4,044	4,381
≥08/09/07	2.39	2.13	2.45	5.48	5.41	5.73
	(0.04)	(0.07)	(0.07)	(0.04)	(0.12)	(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. See Table 1 for further information.

Table 12: Daily LSV 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. See Table 1 for further information.

Table 13: Mean Daily LSV 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 14: Mean Daily LSV Herding Measures - Different Minimum Numbers of Trader Active (2)

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

	All Stocks			DAX 30		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.97 (0.07)	1.67 (0.13)	2.27 (0.13)	3.03 (0.16)	2.76 (0.23)	3.30 (0.23)
Observations	4,171	2,092	2,079	990	491	499
<08/07	1.36 (0.12)	1.35 (0.18)	1.38 (0.16)	3.00 (0.22)	3.18 (0.35)	2.85 (0.28)
Observations	1,710	850	860	410	182	228
≥08/07	2.39 (0.13)	1.89 (0.18)	2.89 (0.20)	3.06 (0.23)	2.52 (0.30)	3.68 (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 16: Mean Monthly LSV 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
≥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. See Table 15 for further information.

Table 17: Mean Quarterly LSV 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. See Table 2 for further information.

Table 18: Mean Daily LSV 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. See Table 1 for further information.

Table 19: 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^{*} (0.0016)	0.0058 (0.0040)	0.0106^{***} (0.0020)
Vol_{it}	0.0122^{***} (0.0006)	0.0170^{***} (0.0018)	0.0098^{***} (0.0106)
$\|r_{i,t-1}\|$	0.0006^{**} (0.0002)		
$r_{i,t-1}$		-0.0004^{**} (0.0002)	0.0003^{*} (0.0001)
Std_{it}	0.0015^{**} (0.0007)	-0.0018 (0.0012)	0.0014^{**} (0.0008)
$Dummy^{b}_{i,t}$		0.0151^{***} (0.0011)	
$Dummy^{s}_{i,t}$			0.0138^{***} (0.0011)
Diagnostics			
$Wooldridge$	$F = 1.298$ ($Prob>F$=0.2568)	$F = 3.077$ ($Prob>F$=0.0882)	$F = 3.454$ ($Prob>F$=0.0855)
$Cook - Weisberg$	$\chi^2 = 3869.82$ ($Prob>\chi^2$=0.0000)	$\chi^2 = 1625.79$ ($Prob>\chi^2$=0.0000)	$\chi^2 = 1562.91$ ($Prob>\chi^2$=0.0000)
$Sargan - Hansen$	$\chi^2 = 18.188$ ($Prob>\chi^2$=0.0011)	$\chi^2 = 39.766$ ($Prob>\chi^2$=0.0000)	$\chi^2 = 15.107$ ($Prob>\chi^2$=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. $Dummy^{b}_{it}$ ($Dummy^{s}_{it}$) is a dummy variable, that equals one, if buy herding (sell herding) occurred also on the previous day $t-1$, and zero otherwise. 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.

Table 20: Mean Sias Measure of 40 Most Active German Banks

	Average Correlation	Partitioned Correlation	
		Follow own trades	Follow trades of others
Whole sample	15.46 (0.36)	10.19 (0.23)	5.27 (0.26)
<08/09/07	15.54 (0.59)	11.51 (0.29)	4.03 (0.24)
≥08/09/07	15.33 (0.47)	9.32 (0.28)	6.01 (0.23)
Buy Herding			
Whole sample	5.73 (0.23)	3.75 (0.11)	1.98 (0.15)
<08/09/07	5.59 (0.37)	4.04 (0.21)	1.55 (0.15)
≥08/09/07	5.83 (0.35)	3.56 (0.15)	2.27 (0.15)
Sell Herding			
Whole sample	9.73 (0.24)	6.45 (0.15)	3.28 (0.12)
<08/09/07	9.95 (0.33)	7.47 (0.26)	2.48 (0.12)
≥08/09/07	9.50 (0.35)	5.76 (0.18)	3.74 (0.13)

Notes: This Table reports results of the Sias measure for all stocks in the samples but considering only the 30 most active institutions. The upper part of the table reports values of the average correlation in percentage terms of the coefficient β. The correlations where first estimated with a cross-sectional regression for each day t and stocks i. The reported correlations display the time-series average of the regression coefficients in percentage terms. The second and third column report the partitioned correlations that result from institutions following their own trades and institutions follow the trades of others, see Equation (7). In the lower parts of the table the correlation is partitioned into those stocks institutions purchased at the previous day (buy herding) and those institutions sold (sell herding). Standard errors are given in parentheses.

Diskussionsbeiträge
des Fachbereichs Wirtschaftswissenschaft
der Freien Universität Berlin

2010

2010/1 BÖNKE, Timm / Sebastian EICHFELDER
Horizontal equity in the German tax-benefit system
Economics

2010/2 BECKER, Sascha / Dieter NAUTZ
Inflation, Price Dispersion and Market Integration through the Lens of a Monetary Search Model
Economics

2010/3 CORNEO, Giacomo / Matthias KEESE / Carsten SCHRÖDER
The Effect of Saving Subsidies on Household Saving
Economics

2010/4 BÖNKE, Timm / Carsten SCHRÖDER / Clive WERDT
Compiling a Harmonized Database from Germany's 1978 to 2003 Sample Surveys of Income and Expenditure
Economics

2010/5 CORNEO, Giacomo
Nationalism, Cognitive Ability, and Interpersonal Relations
Economics

2010/6 TERVALA, Juha / Philipp ENGLER
Beggar-Thyself or Beggar-Thy-Neighbour? The Welfare Effects of Monetary Policy
Economics

2010/7 ABBASSI, Puriya / Dieter NAUTZ
Monetary Transmission Right from the Start: The (Dis)Connection Between the Money Market and the ECB's Main Refinancing Rates
Economics

2010/8 GEYER, Johannes / Viktor STEINER
Public pensions, changing employment patterns, and the impact of pension reforms across birth cohorts
Economics

2010/9 STEINER, Viktor
Konsolidierung der Staatsfinanzen
Economics

2010/10 SELL, Sandra / Kerstin LOPATTA / Jochen HUNDSDOERFER
Der Einfluss der Besteuerung auf die Rechtsformwahl
FACTS

2010/11 MÜLLER, Kai-Uwe / Viktor STEINER
Labor Market and Income Effects of a Legal Minimum Wage in Germany
Economics

2010/12 HUNDSDOERFER, Jochen / Christian SIELAFF / Kay BLAUFUS / Dirk KIESEWETTER / Joachim WEIMANN
The Name Game for Contributions – Influence of Labeling and Earmarking on the Perceived Tax Burden
FACTS

2010/13	MUCHLINSKI, Elke Wie zweckmäßig ist das Vorbild der Physik für ökonomische Begriffe und Metaphern *Economics*
2010/14	MUCHLINSKI, Elke Metaphern, Begriffe und Bedeutungen – das Beispiel internationale monetäre Institutionen *Economics*
2010/15	DITTRICH, Marcus und Andreas Knabe Wage and Employment Effects of Non-binding Minimum Wages *Economics*
2010/16	MEIER, Matthias und Ingo Weller Wissensmanagement und unternehmensinterner Wissenstransfer *Management*
2010/17	NAUTZ, Dieter und Ulrike Rondorf The (In)stability of Money Demand in the Euro Area: Lessons from a Cross-Country Analysis *Economics*
2010/18	BARTELS, Charlotte / Timm Bönke German male income volatility 1984 to 2008: Trends in permanent and transitory income components and the role of the welfare state *Economics*
2010/19	STEINER, Viktor / Florian Wakolbinger Wage subsidies, work incentives, and the reform of the Austrian welfare system *Economics*
2010/20	CORNEO, Giacomo Stakeholding as a New Development Strategy for Saudi Arabia *Economics*
2010/21	UNGRUHE, Markus / Henning KREIS / Michael KLEINALTENKAMP Transaction Cost Theory Refined – Theoretical and Empirical Evidence from a Business-to-Business Marketing Perspective *Marketing*
2010/22	POWALLA, Christian / Rudi K. F. BRESSER Performance Forecasts in Uncertain Environments: Examining the Predictive Power of the VRIO-Framework *Strategic Management*
2010/23	KREMER, Stephanie Herding of Institutional Traders: New Evidence from Daily Data *Economics*