On the Causes and Consequences of Short-Term Herding by Institutional Traders

Stephanie Kremer*
Freie Universität Berlin

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Abstract

This paper provides new evidence on the causes and consequences of herding by institutional investors. The analysis is based on a new and comprehensive database of every transaction made by financial institutions in the German stock market. We confirm that institutions exhibit herding behavior even on a daily basis. Panel regressions reveal that herding behavior is mainly unintentional, most likely due to financial institutions using similar risk models. Evidence of return reversals indicates a destabilizing impact of sell herding. Since those sell herds are the result of institution-wide reaction to commonly used risk measures, our results provides justification for regulators taking a macro-prudential view on risks.

Keywords: Investor Behavior, Institutional Trading, Stock Prices, Herding

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*Department of Economics, Boltzmannstraße 20, D-14195 Berlin, Germany. E-Mail: stephanie.kremer@fu-berlin.de. Support by the Deutsche Forschungsgemeinschaft (DFG) through the CRC 649 "Economic Risk" is gratefully acknowledged. We thank the German Federal Financial Supervisory Authority (Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin)) for providing the data and, in particular, Michael Kollak for his support.The paper does not represent a statement by BaFin. The paper benefited from comments received at the EEA meeting in Glasgow, the FFM conference in Hanover, and the CRC 649 meeting in Motzen.

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. 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 the common reaction on public information and signals (see, e.g., Bikhchandani and Sharma (2001)). Distinguishing the sources of herding is crucial for regulatory purposes and in discovering whether herding leads to market inefficiency and/or financial bubbles. In particular, *intentional herding* 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)). But also *unintentional herding* may be inefficient for the market, if not driven by fundamental values.

The aim of this paper is to shed more light on the herding behavior of institutional investors, in particular banks. The predominant class of investors in the stock market has the power to move the market and impact prices, even more if they herd. This emphasizes the importance of discovering whether institutional investors herd and, if so, the *causes* and the *consequences* of herd behavior for stock prices.

To date, the literature on institutional herding has been severely handicapped by the unavailability of appropriate 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)). Studies employing this type of data are also limited in the investigation of the determinants and the price impact 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).[1]

This paper contributes to the empirical literature on herding by using higher-frequency investor-level data that directly identify institutional transactions. The analysis therefore overcomes the data problems faced by previous studies and provides new evidence on the short-term herding behavior of financial institutions for a broad cross-section of stocks over the period from July 2006 to March 2009 in the German stock market.[2] Advancing on previous descriptive approaches, the availability of daily, investor-specific data enables us to perform a panel econometric analysis of the causes of herding and its consequences on stock prices.

The estimation results reveal that financial institutions do indeed herd and that this herding depends on stock characteristics as well as on past returns and stock volatility. In particular, we find –contrary to the theory of *intentional* herding– 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. Our panel regression reveal further evidence that herding is rather of the *unintentional* type. For instance, herding on the buy and sell side is inverse related to past returns. Interestingly, only herding on the sell side is positively related to past stock volatility. This finding can be explained by the common use of risk measures that drives correlated sell activities after a rise in volatility.

Even herding can mainly be explained by *unintentional* sources, non-fundamental factors can result in a destabilizing impact. The literature explores a destabilizing stock price impact by investigating whether subsequent returns continue or reverse after herding activities. Destabilizing herding, driving prices away from fundamental values, would result in subsequent return reversals, see, e.g., Choi and Sias (2009). In fact, by investigating subsequent stock returns in relation to buy herding and sell herding

[1] 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. Kremer and Nautz (2010) show that this approach can lead to misleading conclusions.

[2] Walter and Weber (2006) analyzed herding for German mutual funds at a semi-annual frequency.

activity, we find evidence for an destabilizing impact of sell herds but not of buy herds: The negative impact of sell herding on stock returns reverse after a few trading days, while in case of buy herding the positive impact continuous.

Our results provide evidence of a destabilizing impact of sell herds in the German stock market. Since those sell herds are the result of institution-wide reaction to commonly used risk measures, this evidence provides justification for regulators taking a macro-prudential view of risk. In line with the predictions of Persaud (2000) and Daníelsson (2008), regulators and risk modeling institutions should take into account the endogeneity of risks induced by similar market-sensitive risk management systems.

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

2 Theory and Empirical Literature

2.1 Types of 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 *i) intentional herding* and *ii) unintentional*, or *spurious herding* (see, e.g., Bikhchandani and Sharma (2001)).

Unintentional herding arises because institutions are attracted by stocks with certain characteristics such as higher liquidity (see, e.g., Falkenstein (1996)) or because institutions 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. A prominent example is the common reaction of financial institutions on similar risk measures.

In contrast, *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. Two major theoretical models explain the rational behind this behavior: 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. 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.

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 Causes of Herding

Distinguishing between different causes or types 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. Moreover, theories of why institutions herd are not mutually exclusive.

2.2.1 Market Transparency

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

Lakonishok et al. (1992) investigate herding within a quarterly time span using a sample of U.S. equity funds. They 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 in favor of *intentional herding*. Conversely, *unintentional herding* is more likely to occur in stocks with larger market capitalization because institutions have a higher commonality in information. In fact, Lakonishok et al. (1992) find evidence of herding being more intense among small companies compared to large stocks. Other studies, e.g., Wermers (1999), Sias (2004) or Choi and Sias (2009) confirm higher herding in small stocks.

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.[3] High herding in emerging markets may be attributed to incomplete regulatory frame-works, 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.

[3] 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)). 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.

2.2.2 Feedback Trading

As unintentional herding occurs due to simultaneous reaction to a common signal, a manifestation of this kind of herding is momentum investment, i.e., *positive feedback trading*. If herding is driven by past returns, this would be interpreted as evidence of unintentional herding, see, e.g., Froot, Scharfstein and Stein (1992); and Sias (2004). The evidence on feedback trading to date is mixed. Lakonishok et al. (1992) show that past performances of stocks does not increase herding; Grinblatt, Titman and Wermers (1995) document positive feedback strategies that do contribute to herding. In contrast, Wylie (2005) finds that U.K. funds herd out of stocks that have performed well in the past. Even though herding caused by correlated positive feedback trading is considered to be unintentional herding, it still could have a destabilizing impact on financial markets, see, e.g., De Long, Shleifer, Summers and Waldmann (1990).

2.2.3 Risk Management Systems

Persaud (2000), Jorion (2002), and Daníelsson (2008) argue that *market-sensitive* risk management systems used by banks, such as Value at Risk (VaR) models, require banks to sell when 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. If financial regulation implies that institutions are increasingly using similar market-sensitive risk management systems, *unintentional* herding occurs because the diversity of decision rules is reduced.

2.3 Revealing a Destabilizing Price Impact

Institutional herds may induce price pressure and thus impact stock prices. However, this might not necessarily destabilize the market. In particular *unintentional* herding can be an efficient outcome, provided it results from the simultaneous reaction on fundamental values. In this case, it speeds up the adjustment of prices and make the market more efficient, see Lakonishok et al. (1992). In contrast, both types of herding lead to inefficient outcomes if not based on fundamentals. In this case, asset prices fail to reflect fundamental information. Herding then causes a 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)).

Scharfstein and Stein (1990) and Barberis and Schleifer (2003) suggest that herding not based on fundamental values may drive prices away from fundamentals which results in subsequent return reversals. In order to reveal a destabilizing impact empirically one has to detect whether the impact of herding on prices continues or reverse in the future while the latter would be interpreted as destabilizing impact, see, e.g., Choi and Sias (2009).

Previous evidence on this issue is rather mixed: Early studies based on quarterly data, e.g., Lakonishok et al. (1992), Wermers (1999) or Sias (2004) don't find return reversals following herds, while more recent studies, e.g. Puckett and Yan (2008) and Brown, Wei and Wermers (2010) provide evidence on return reversals implying a destabilizing impact of herding. Puckett and Yan (2008) partially overcome the low-frequency problem of previous studies by using weekly data. They argue that a destabilizing effect of herding is more likely to be detected in the short horizon since the market will dissipate deviations from fundamental values through, e.g., actions of arbitrageurs. Studies based on quarterly data are not able to detect destabilizing impacts over shorter horizons.

In Section 6 we will investigate subsequent returns after herding activity and provide evidence on reversals or continuation of the impact of herding on subsequent returns.

3 The Dataset

Because the dataset employed in this paper includes all real-time transactions carried out on German stock exchanges, most of the problems that plague earlier work are avoided. 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 make it possible to identify 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 specify on whose behalf the trade was executed, i.e., whether the institution traded for its own account or on behalf of a client that is not a financial institution. Since this study is chiefly concerned with 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. We also exclude institutions that are formally mandated as designated sponsors, i.e., liquidity providers, for a specific stock.[4]

Using data from July 2006 to March 2009 (698 trading days), we cover market upturns as well as the recent market downturn. We investigate whether trading behavior has changed since the onset of the financial crises.

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]

[4] For each stock, there are usually about two institutions formally mandated as market maker. The institutions are not completely dropped from the sample (unless have already been dropped due to purely engaging in market maker business), but only for those stocks for which they act as designated sponsors. The particular designated sponsors for each stock are published at www.deutsche-boerse.com.

[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. We require at least five institutions active each day, decreasing the sample to 83,842 remaining observations.

These indices allow to investigate the trading behavior in small and large stocks.

Over the observation period, we have proprietary transactions by 1,120 institutions involving those stocks on German stock exchanges.[6] For each institution, we compute the daily trade imbalance. On average, about 25 of these institutions trade every day in those stocks, justifying the use of daily data. Table **??** in the Appendix provides further information.

Kremer and Nautz (2010) investigate the entire sample of those 1,200 financial institutions in the German stock market;[7] this paper focuses on particularly important 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 from a more homogenous group of professionals who are evaluated against each other, see Scharfstein and Stein (1990). The overall sample of 1,120 institutions is a large heterogeneous group. Among those 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. Hence, the detection of any destabilizing impact would suggest a high potential threat to financial stability. Moreover, these professionals can be considered as peers.

We therefore built a subsample based on the 30 most active traders.[8] This subgroup includes several foreign institutions. We therefore create an additional subsample comprised of only the 40 most active German banks that are engaged in proprietary trading on stock markets.[9] The German banks are all subject to the same regulatory regime

[6]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.

[7]Kremer and Nautz (2010) focus on the impact of data frequency on herding measures, but not on causes and consequences of herding.

[8]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.

[9]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

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 the risk reports included in their annual reports– that they all use VaR models and implement regulatory or internal VaR limits.

4 Do Institutions Herd?

4.1 The Herding Measures

Following the bulk of the empirical literature, our analysis builds on 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.[10]

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.[11] Consider a number of N_{it} institutions trading in stock i at time t. Out of these N_{it} transactions, a number of b_{it} are buy transactions. The buyer ratio br_{it}, the prominent variable in the LSV measure, is then defined as $br_{it} = \frac{b_{it}}{N_{it}}$.

The second import variable is $\bar{br}_t$, i.e. the average of the buyer ratio over all stocks at time t. This variable accounts for an overall signal in the market at t.

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.

[10] An alternative measure used in the literature is that constructed by Sias (2004). This dynamic measure quantifies the degree to which institutions follow institutional trades of the prior period. The Sias herding measure captures the degree of correlation of the fraction of buyers between different periods. We will show results on the Sias measure in the Appendix, see Table 9. The results do not effect our main conclusions. When revealing determinants and consequences of herding in this study we will focus on the LSV herding measure, since previous studies (and also Sias (2004)) use static measures capturing intra-period herds for determining price impacts.

[11] One implication of this assumption is that short selling must be possible. This assumption is not problematic for our investigated institutions, for which short selling is in general feasible. In contrast, most mutual funds investigated by previous studies are not allowed to 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.

In line with the definition of herding above, the LSV herding statistic is given by

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

The first term captures the deviation of the buyers ratio in stock i at t from the overall buy probability at time t. Thus, herding is measured 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 second term $E_t[|br_{it} - \bar{br}_t|]$ is the expected value of the difference between the buyer ratio and period-average buyer ratio. Subtracting this term accounts for the possibility to observe more variation in the buyers ratio in stocks with only a few trades. This adjustment factor ensures that the herding measure HM_{it} will be zero if the trades are independent.[12]

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 have been expected if each trader had decided randomly and independently. Note that the maximum value of $\overline{HM}$ is not equal to 100%, 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.

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, where

[12] Following previous studies, e.g., Wermers (1999), HM_{it} is computed only if at least five traders are active in i at time t, however, the loss of observations is not relevant, see Section 3. Estimations with different minimum numbers of traders (up to 20) reveal that results are robust with respect to the assumptions on minimum numbers of traders. Results are available on request.

$$BHM_{it} = HM_{it} \quad if \quad br_{it} > \bar{br}_t, \tag{2}$$

$$SHM_{it} = HM_{it} \quad if \quad br_{it} < \bar{br}_t. \tag{3}$$

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.[13]

BHM_{it} and SHM_{it} capture 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 causes of trading behavior in Section 5.2.

4.2 Herding of Institutions in the German Stock Market

Table 1: 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	4,546	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. 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.

[13]Comparing the observations in, e.g., Table 3, the resulting loss of data is not empirically relevant.

Results provided in Table 1 reveal higher herding measures for the 30 most active traders compared to the findings of Kremer and Nautz (2010) for all institutions. The mean daily herding measure across all stocks is 2.48%. Considering only DAX 30 stocks, the herding measure significantly rises to 5.18%, a high level of herding compared to previous findings. For MDAX and SDAX stocks, the herding measure is small, see Table 6 in the Appendix. This result does not support the theory of *intentional* herding, which predicts higher herding levels in stocks with less information availability and asymmetry. This suggests that herding behavior is more likely of the *unintentional* type.

There is no evidence for increased herding during the crisis period. Herding on the buy side is more pronounced in the non-crisis period, whereas sell side herding is higher than buy herding during the crisis. This might be a result of higher volatility of stocks during the financial crisis. Our panel econometric analysis in Section 5.2 shall provide more insights into this issue.

The results for the sample of 40 most active German banks are shown in Table 7 and Table 8 in the Appendix. The findings are very 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%, confirming the hypothesis that herding might be more of the unintentional type.[14]

5 Why do Institutions Herd?

5.1 Possible Causes of Herding

In this Section we investigate the potential causes of the herding behavior detected in the previous Section within a panel estimation framework. 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

[14]Results on the Sias measure displayed in Table 9 and Table 10 in the Appendix do not effect those conclusions. In fact, results show that the main part of the estimated correlation of trades stems from institutions that follow their own trades rather than following others.

uncertainty. On the other hand, *unintentional* herding is related to reliable public information. The following empirical analysis therefore focuses on empirical proxies to measure information availability, information asymmetry or uncertainty in the market. Moreover, the focus is on determinants that may imply a destabilizing pro-cyclicality.

Information Availability

Following the previous literature on herding, we consider firm size ($Size$) as 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. Conversely, unintentional herding is more likely to occur in larger stocks because institutions have a higher commonality in information. Firm size is measured by the logarithm of the previous day's closing market capitalization of the specific stock.

Information Asymmetry

A factor also 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. We therefore use market volumes of stocks[15] as a proxy for information asymmetry and expect, based on intentional herding theory, that lower trading volumes are associated with higher herding levels. Conversely, a positive relation could be explained by herding of institutions that are attracted by stocks with higher liquidity (see, e.g. Falkenstein (1996)).

[15] Leuz and Verrecchia (2000) and Welker (2006) argue that market liquidity can be measured by transaction volumes or bid-ask spreads.

Uncertainty vs. Risk Measures

Additionally, we compute stock return volatility (Std) based on the standard deviation of the past 250 daily stock returns and on the last 90 and 30 stock returns. 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 higher herding in stocks that experienced a higher degree of volatility. Note that higher information uncertainty should induce herding in a symmetric way, i.e., 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 risk measures. VaR models or other volatility sensitive models employed for risk management purposes and regulatory requirements induce common sell activity, see e.g. Persaud (2002). The minimum observation period according to Basel II market risk standards is one year, i.e., 250 trading days. Therefore, we expect to see more sell herding in stocks with higher past year standard deviation of stock returns, since those regulated institutions highly engaged in trading generally use such risk management models or at least built on past volatility as risk measure.[16] A positive impact of volatility on sell herding but not on buy herding could then be considered as evidence of unintentional herding.

Feedback Trading

We further 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).

[16] For all German banks in the sample, we can ensure that VaR models and implement regulatory or internal VaR limits are used according to statements in their risk reports included in annual reports.

Table 2 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 2: Theoretical Predictions on the Determinants of Herding

	Intentional	Unintentional
$Size$	$-$	$+$
Vol	$-$	$+$
r	0	$+/-$
Std	$+$ for buy and sell herding	$-$ only for sell herding

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

5.2 On the Causes of Herding: Empirical Results from Panel Regressions

5.2.1 Empirical Determinants of Herding Behavior

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

$$HM_{it} = a + bSize_{i,t-1} + cVol_{it} + d|r_{i,t-1}| + eStd_{it} + \alpha_i + \gamma_t + \epsilon_{it}, \qquad (4)$$

where HM_{it} is the LSV herding measure of the 30 most active traders as calculated according to Equation (1).[17] $Size_{i,t-1}$ 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 $t-2$.[18] The

[17] Results considering the herding measures for the 40 German banks are very similar. For brevity results are not displayed but are available on request.

[18] We include further lagged return measures to check robustness.

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.[19] α_i are stock-specific effects and γ_t are time dummies.[20]

Let us first look at the results for the regression with the unsigned herding measure HM, which are displayed in the first column of Table 3. The coefficient estimate for $Size$ is positive but insignificant and the coefficient for Vol is positive and statistically significant. This suggests that the evidence of higher herding levels for DAX 30 stocks in Section 4.2 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.[21] Second, since higher trading volume is related to lower information asymmetry and higher information quality, this result suggests that these large financial institutions are less likely to engage in *intentional* herding. The positive relation could be an indication of *unintentional* herding, whereby the institutions are attracted by stocks with specific characteristics like higher trading volume, see Falkenstein (1996).

The parameter estimate for volatility of returns Std indicates that there is more herding for more volatile stocks. Volatility in the market is related to uncertainty and thus, at first glance, this estimate hints at the existence of *intentional* herding. However, the estimate could also be related to the common use of risk measures that recommend selling the more volatile stocks. Results on buy and sell herding discussed below shed more light on this issue.

5.2.2 Buy and Sell Herding

The variables described above might affect buy and sell herding differently. We therefore estimate Equation (4) separately for herding on the buy and sell side using the same set

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[19] We include different volatility measures to check robustness.

[20] 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.

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

Table 3: Causes of Herding - Panel Regression

	HM_{it}	BHM_{it}	SHM_{it}
Regressors			
$Size_{i,t-1}$	0.0020 (0.0027)	0.0029 (0.0020)	0.0016 (0.0019)
Vol_{it}	0.0069*** (0.0012)	0.0023*** (0.0007)	0.0082*** (0.0008)
$\|r_{i,t-1}\|$	-0.0001 (0.0003)		
$r_{i,t-1}$		-0.0015*** (0.0002)	0.0008*** (0.0002)
Std_{it}	0.0031*** (0.0012)	-0.0096*** (0.0009)	0.0020*** (0.0012)
$Dummy_{it}^b$		0.0156*** (0.0011)	
$Dummy_{it}^s$			0.0111*** (0.0002)
Diagnostics			
$Wooldridge$	$F = 0.346$ ($Prob > F$=0.5573)	$F = 0.251$ ($Prob > F$=0.6170)	$F = 0.666$ ($Prob > F$=0.4159)
$Cook - Weisberg$	$\chi^2 = 3383.14$ ($Prob > \chi^2$=0.0000)	$\chi^2 = 4924.52$ ($Prob > \chi^2$=0.0000)	$\chi^2 = 1290.95$ ($Prob > \chi^2$=0.0000)
$Sargan - Hansen$	$\chi^2 = 10.343$ ($Prob > \chi^2$=0.0350)	$\chi^2 = 16.422$ ($Prob > \chi^2$=0.0353)	$\chi^2 = 17.536$ ($Prob > \chi^2$=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} are 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. $Dummy_{it}^b$ ($Dummy_{it}^s$) 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.

of explanatory variables. The only exception is 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:

$$BHM_{it} = a^b + b^b Size_{i,t-1} + c^b Vol_{it} + d^b r_{i,t-1} + e^b Std_{it} + e^b Dummy_{it}^b + \alpha_i^b + \gamma_t^b + \epsilon_{it}^b \quad (5)$$

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

In these regressions we also include a dummy variable $Dummy_{it}^b$ ($Dummy_{it}^s$), equal to one, if buy herding (sell herding) also occurred on the previous day $t-1$; zero otherwise.[22]

The results for the fixed effects regressions on buy and sell herding are reported in the second and third columns of Table 3. Estimates for Vol reveal that herding on the buy and sell sides is positively related to the liquidity of stocks. In line with Sias (2004), the small but significant impact of the dummy variables shows that herding is persistent over time.

The results obtained for r and Std are particularly interesting. First, the signs of Std differ between the buy and sell herding regression. 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. However, the coefficient estimate for Std on buy herding is significantly negative. This asymmetric effect is not compatible with the theory of *intentional* herding. It is unlikely that the herding behavior is 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

[22] These dummies partly account for persistence of herding on either the buy or sell side. To account for a correlation is suggested by the evidence on the Sias measure in Table 9. We include dummy variables rather than the lagged endogenous variable to avoid too many missing observations. Note also that the exclusion of those dummies would not impact our main results since it would not change the significance or the signs of the other covariates.

common risk management practices, see Daníelsson (2008).[23]

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.[24]

The lower part of Table 3 presents the relevant test statistics and p-values of diagnostic tests. The three models Equations (4) - (6) 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.[25] We account for heteroscedasticity in the error terms, by using heteroscedasticity-robust standard errors, see Stock and Watson (2008).

[23]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 (often used as internal risk measures) does not change the results significantly. For brevity, these results are not presented, but are available on request.

[24]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 cumulative 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.

[25]According to a Hausman test on endogeneity of the regressors, the null hypothesis of exogeneity cannot be rejected. However, results are consistent with respect to Generalized Method of Moments (GMM) estimations.

6 On the Consequences of Herding on Stock Prices

6.1 Empirical Results from Panel Regressions

Our evidence implies that institutions rather herd unintentionally. However, even unintentional herding may contribute to destabilization if not based on fundamental information. In order to examine whether herding is stabilizing or destabilizing, theoretical predictions (see Section 2.3) and previous empirical studies (see e.g. Sias (2004)) suggest to analyze whether the relation of herding and subsequent prices continues or reverses.

If herding does reflect the incorporation of fundamental information into asset prices, a positive (negative) correlation of buy (sell) herding and subsequent returns should continue. In contrast, if herding drives stock prices away from fundamental values, as it is not information based, we would expect evidence of reversals in subsequent periods. To investigate the impact of herding and subsequent returns, we estimate the following fixed effects panel regression models:

$$\begin{aligned} r_{i,t,t+n} &= a^n + b^n BHM_{it} + c^n SHM_{it} + d^n Size_{it} \\ &+ e^n BM_{it} + f^n r_{i,t,t-5} + g^n Std_{it} + \alpha_i^n + \gamma_t^n + \epsilon_{it}^n, \end{aligned} \tag{7}$$

where $r_{i,t,t+n}$ denotes the cumulative return of stock i from time t to $t+n$. Cumulative returns are calculated for $n = 1, 2, ..., 20$ trading days, i.e., the one day ahead return ($n = 1$), and cumulative returns during subsequent two, three,.., or 20 days. In line with Puckett and Yan (2008) and Barber et al. (2009), we include in Equation (7) control variables $Size_{it}$, measured by the logarithm of closing market capitalization of stock i, the book-to-market ratio BM_{it} of stock i, $r_{i,t,t-5}$, the past cumulative return of stock i measured from the closing prices on day t and $t-5$ and Std_{it}, measured as the standard deviation of the past 250 daily stock returns.[26] Heterogenous stock-specific

[26] Again, we include 90 and 30 days Std to check robustness. We also test again for alternative lagged

effects α_i and time dummies γ_t are also included in the regression.[27]

Table 4: Consequences of Herding - Panel Regression (1)

	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
BHM_{it}	0.216	0.633***	0.872***	1.002***	1.348***	1.600***
	(0.146)	(0.256)	(0.302)	(0.039)	(0.239)	(0.734)
SHM_{it}	−0.445***	−0.641***	−0.751***	−0.587**	0.674	0.698
	(0.182)	(0.295)	(0.258)	(0.289)	(0.429)	(0.662)

Notes: This table presents results of regressions of future stock returns on institutional herding. Six regressions of Equation (7) with different cumulative future returns (up to $n = 20$ trading days) as dependent variable are estimated. The subsequent cumulative return is regressed on the buy herding measure BHM_{it}, the sell herding measure SHM_{it} and control variables $Size_{it}$, BM_{it}, Vol_{it}, $r_{i,t,t-5}$ and Std_{it}, see Table 3 for explanation. The statistical significance at 1%, 5%, and 10% is represented as ***, **, and * respectively. Standard errors are given in parentheses. Results for the complete set of regressors are displayed in Table 11 in the Appendix.

To account for endogenous returns $r_{i,t,t-5}$, we estimate the regression with GMM using lagged variables as instruments. Hansen J statistics confirm the validity. However, due to the large T, the endogeneity bias is negligible and results are again consistent across estimation methods.[28] We account for heteroscedasticity and autocorrelation in the error terms by using robust standard errors, see Stock and Watson (2008). The lower part of Table 11 in the Appendix presents test statistics and p-values of diagnostic tests.

We perform the panel regressions of Equation (7) twenty times, i.e., for each n. The six columns in Table 4 display the results for the different cumulative returns n= $1, 2, 3, 5, 10, 20$ as dependent variables. First, the coefficients on BHM_{it} are positive and significant over the complete time horizon. In line with Puckett and Yan (2008) this finding does not imply any destabilizing reversal after buy herding. In the short-term for the first subsequent days, coefficients on SHM_{it} are significantly negative.

return specifications, with $r_{i,t-1}$ up to $r_{i,t-5}$. Results do not change qualitatively and are available upon request.

[27]A Breusch-Pagan Lagrange multiplier test on $H_0 : \sigma_i^2 = 0$ indicates the existence of individual effects α_i. The inclusion of time dummies γ_t does not change the results.

[28]For brevity, OLS results are not presented, but are available on request.

However, for the cumulative returns after 10 trading days, the sign changes to positive and the coefficient estimate becomes insignificant.[29] In accordance with Puckett and Yan (2008) this reversal in the relation of sell herding and cumulative returns imply a destabilizing effect of sell herding by institutions.

Findings on the remaining control variables, displayed in Table 11 in the Appendix, are consistent with earlier findings, e.g., Puckett and Yan (2008): Subsequent returns are negatively related to prior returns $r_{i,t,t-5}$ and firm size $Size_{i,t}$, implying that small stocks outperform large stocks. Moreover, past volatility Std_{it} has also a negative effect on subsequent returns.

6.2 Portfolio Formation Results

In order to demonstrate the robustness of our findings, we follow Wermers (1999) and related empirical literature and investigate subsequent abnormal returns of stock that institutions have heavily bought and sold in herds. For each day, all stocks are categorized into buy-herding or sell-herding stocks. For both groups, stocks quintile portfolios are formed based on their daily herding measures. Thus, portfolio B1 (B5) consists of stocks that have a small (high) value of BHM_{it}, while stocks in S1 (S5) have a small (high) value of SHM_{it}. For each of the ten constructed portfolios daily subsequent mean abnormal returns ar_{t+n} were calculated with Fama-French factor alphas.[30] In line with Puckett and Yan (2008), daily abnormal returns were calculated and then averaged for $n = 1, 2...20$ days, i.e. ar_{20} represents the average abnormal daily return during the first 20 trading days.

[29]In fact, the coefficient estimate decrease at $n = 5$, gets insignificant at $n = 7$, and the change of the sign occurs at $n = 9$. Results are not reported for brevity, but are available on request.

[30]Using the following regression:

$$r_{p,t} = \alpha_p + \beta_{1p}RMRF_t + \beta_{2p}SMB_t + \beta_{3p}HML_t + \epsilon_{pt}.$$

Factors $RMRF_t$, SMB_t and HML_t are calculated following the portfolio construction procedure described by Fama and French. To calculate excess market return $RMRF_t$, we use daily returns of the Composite DAX (CDAX), covering all stocks in the general and prime standard. As risk free rate, we use daily data on annualized 3-month money market rates in Germany available from the Deutsche Bundesbank.

Table 5: Consequences of Herding - Portfolio Abnormal Returns

	ar_1	ar_2	ar_3	ar_5	ar_{10}	ar_{20}
Buy Herding						
B1	-0.024	0.001	0.008	-0.001	-0.006	0.022
B2	0.014	0.014	0.021	0.019	0.003	0.001
B3	0.029	0.004	-0.011	0.001	-0.003	-0.006
B4	0.048	0.049	0.029	0.020	0.013	0.006
B5	0.046	0.046	0.053	0.036	0.015	0.017
Sell Herding						
S1	0.012	-0.006	-0.009	-0.006	-0.005	-0.004
S2	-0.021	-0.003	-0.019	-0.016	-0.014	-0.005
S3	-0.021	-0.027	-0.021	-0.002	0.078	0.003
S4	-0.045	-0.037	-0.032	-0.021	-0.021	0.009
S5	-0.043	-0.044	-0.018	-0.012	0.001	0.011

Notes: For each time period t, all stocks are sorted by institutional buying-herding measures BHM_{it}, forming portfolios B1 to B5, or by selling-herding measures SHM_{it}, forming portfolios S1 to S5. Then we calculate the mean abnormal returns for the 10 herding-sorted portfolios. B5 (S5) represents the portfolio where stocks are heavily bought (sold) by herd while B1 (S1) represents the portfolio where stocks are lightly bought (sold) by herd. For each of the ten constructed portfolios daily abnormal returns ar_{t+n} were calculated with Fama-French factor alphas. Finally, the time-series average abnormal return for each portfolio is computed for $n = 1, 2, ..., 20$ days. Abnormal returns are calculated and are presented in percentage terms.

Results presented in Table 5 confirm conclusions of the panel regression analysis. The six columns in the table display the results for the different average abnormal returns for days n= $1, 2, 3, 5, 10, 20$. The highest buy herding portfolios show on average up to 20 trading days positive daily abnormal returns. However, abnormal daily returns strongly decrease after three days. In fact, the factor alphas according to the Fama-French regression get insignificant but are still positive after the fourth day.[31] For the highest sell herding portfolios (S4 and S5) daily abnormal returns are negative for the first few days after herding. Again, the effect decreases. Factor alphas get insignificant and change to positive values after five trading days. Towards ten trading days even the average of the daily abnormal returns as shown in the fifth column of Table 5 change

[31] Results for the single Fama-French regressions are not displayed for brevity, but are available on request.

to positive values.

7 Conclusion

This paper contributes to the empirical literature on herding by using higher-frequency investor-level data that directly identify institutional transactions. The analysis therefore 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 explore causes and consequences of herding by financial institutions.

Contradicting the theory on intentional herding, 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 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.

A panel econometric analysis confirms this conclusion and provides further insight into the causes 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. Most important, we find that rising stock volatility leads to more sell-side herding by financial institutions. This result indicates, that herding results also from the common reaction of institutions on risk measures.

Regarding the consequences of herding, we show that sell-side herding is attributed to a destabilization of stock prices in the short-term, as indicated by subsequent return reversals after sell herding.

The empirical results of the paper therefore support the predictions of Daníelsson (2008) and Daníelsson, Shin and Zigrand (2009), who argue that the common use of VaR models and other volatility sensitive risk measures reduce the diversity of decision rules resulting in herding behavior by banks with potential destabilizing implications. Therefore, regulators and risk modeling institutions need to be aware of how risk management systems induce risk endogeneity and affect macro-prudential aspects of risks.

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A Appendix

Table 6: 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 the 30 most active institutions in the sample. See Table 1 for further information.

Table 7: 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 (0.03)	2.11 (0.05)	2.31 (0.05)	5.21 (0.05)	5.05 (0.08)	5.30 (0.08)
Observations	69,274	34,573	34,694	20,897	10,132	10,764
<08/09/07	1.96 (0.05)	2.07 (0.04)	1.85 (0.08)	4.78 (0.08)	5.65 (0.09)	4.86 (0.12)
Observations	27,635	13,728	13,907	8,425	4,044	4,381
≥08/09/07	2.39 (0.04)	2.13 (0.07)	2.45 (0.07)	5.48 (0.04)	5.41 (0.12)	5.73 (0.10)
Observations	41,639	20,845	20,787	12,472	6,088	6,383

Notes: This table reports mean values of HM, BHM and SHM in percentage terms for the whole sample of stocks and for DAX 30 stocks considering the 40 largest German banks that are engaged in proprietary trading. See Table 1 for further information.

Table 8: Daily LSV Herding Measures of 40 Most Active German Banks (2)

	MDAX			SDAX		
	HM	BHM	SHM	HM	BHM	SHM
Whole sample	1.22 (0.05)	1.29 (0.07)	1.15 (0.07)	0.22 (0.08)	0.11 (0.12)	0.34 (0.12)
Observations	31,630	16,050	15,575	16,747	8,391	8,355
<08/09/07	1.25 (0.07)	1.40 (0.11)	1.10 (0.10)	0.14 (0.12)	0.31 (0.18)	0.63 (0.17)
Observations	12,072	6,043	6,029	7,138	3,641	3,497
≥08/09/07	1.21 (0.07)	1.22 (0.09)	1.18 (0.08)	0.50 (0.11)	0.04 (0.16)	1.05 (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 the 40 largest German banks that are engaged in proprietary trading. See Table 1 for further information.

Table 9: 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 considering 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 were 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 following the trades of others, see Sias (2004). 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 10: 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 the 40 largest German banks. See Table 9 for further explanation.

Table 11: Consequences of Herding - Panel Regression (2)

	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
Regressors						
BHM_{it}	0.216	0.633***	0.872***	1.002***	1.348***	1.600***
	(0.146)	(0.256)	(0.302)	(0.039)	(0.239)	(0.734)
SHM_{it}	−0.445***	−0.641***	−0.751***	−0.587**	0.674	0.698
	(0.182)	(0.295)	(0.258)	(0.289)	(0.429)	(0.662)
$Size_{it}$	−0.172***	−0.314***	−0.561***	−1.029***	−2.300***	−3.172***
	(0.056)	(0.085)	(0.096)	(0.084)	(0.123)	(0.155)
BM_{it}	0.146***	0.340***	0.522***	1.030***	1.540***	2.075***
	(0.036)	(0.056)	(0.064)	(0.030)	(0.121)	(0.141)
Vol_{it}	0.019	0.026	0.053*	0.030	0.006	0.012
	(0.013)	(0.020)	(0.029)	(0.030)	(0.041)	(0.041)
$r_{i,t,t-5}$	−0.032***	−0.065***	−0.065**	−0.048***	−0.045***	−0.026*
	(0.003)	(0.005)	(0.006)	(0.008)	(0.010)	(0.014)
Std_{it}	−0.223***	−0.458***	−0.602***	−1.122***	−2.162***	−4.166***
	(0.022)	(0.027)	(0.032)	(0.041)	(0.056)	(0.096)
Diagnostics						
$Wool.$	$F = 13.91$	$F = 145.91$	$F = 703.34$	$F = 68.83$	$F = 269.21$	$F = 112.18$
	$(P>F=0.00)$	$(P>F=0.00)$	$(P>F=0.00)$	$(P>F=0.00)$	$(P>F=0.00)$	$(P>F=0.00)$
$C.-W.$	$\chi^2 = 9125.6$	$\chi^2 = 12966$	$\chi^2 = 13244$	$\chi^2 = 14152$	$\chi^2 = 16661$	$\chi^2 = 19318$
	$(P>\chi^2=0.00)$	$(P>\chi^2=0.00)$	$(P>\chi^2=0.00)$	$(P>\chi^2=0.00)$	$(P>\chi^2=0.00)$	$(P>\chi^2=0.00)$
$S.-H.$	$\chi^2 = 36.80$	$\chi^2 = 18.39$	$\chi^2 = 8.93$	$\chi^2 = 12.53$	$\chi^2 = 25.22$	$\chi^2 = 36.29$
	$(P>\chi^2=0.00)$	$(P>\chi^2=0.00)$	$(P>\chi^2=0.01)$	$(P>\chi^2=0.00)$	$(P>\chi^2=0.00)$	$(P>\chi^2=0.00)$

Notes: This table presents the results of the complete set of regressors for regressions of future stock returns on institutional herding. Six regressions of Equation (7) with different cumulative future returns (up to $n = 20$ trading days) as dependent variable are estimated. The subsequent cumulative return is regressed on the buy herding measure BHM_{it}, the sell herding measure SHM_{it} and control variables $Size_{it}$, BM_{it}, Vol_{it}, $r_{i,t,t-5}$ and Std_{it}. The statistical significance at 1%, 5%, and 10% is represented as ***, **, and * respectively. Standard errors are given in parentheses. The lower part of the table reports test statistics and p-values in parentheses ($Wool.$, $C.-W.$, and $S.-H.$ display $Wooldridge$, $Cook-Weisberg$, and $Sargan-Hansen$ tests, see Table 3 for more explanation.