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Causes and consequences of short-term institutional herding

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ABSTRACT

This paper provides new evidence on the causes and consequences of herding by institutional investors. Using a comprehensive database of every transaction made by financial institutions in the German stock market, we show that institutions exhibit herding behavior on a daily basis. Herding intensity depends on stock characteristics including past returns and volatility. Return reversals indicate a destabilizing impact of herds on stock prices in the short term. Results from panel regressions suggest that herding is mainly unintentional and partly driven by the use of similar risk models. Our findings confirm the importance of macro-prudential aspects for banking regulation.

1. Introduction

A growing body of literature established that investors exhibit herding, meaning the tendency of investors to "bunch up" on one side of the market. The literature suggests two major explanations for herding behavior: *intentional* herding occurs whenever traders ignore their own private information and intentionally follow the crowd, since they infer from observed trading behavior that others have superior information. In contrast, *unintentional* herding is mainly driven by widespread identical reaction to public information and signals, see, e.g., Bikhchandani and Sharma (2001). Distinguishing the causes of herding behavior is crucial for regulatory purposes and for discovering whether herding leads to market inefficiency and financial bubbles. According to Scharfstein and Stein (1990), Hirshleifer and Teoh (2003), and Hwang and Salmon (2004), intentional herding may destabilize stock prices and thus impair the proper functioning of financial markets. However, even unintentional herding may be inefficient, if the correlated trading is not driven by fundamental values. The current paper explores the herding behavior of institutional investors, specifically banks. This predominant class of investors in the stock market has the power to move the market and impact prices, particularly if they herd. This explains why it is important to investigate whether institutional investors herd and, if so, the causes and the consequences of herd behavior for stock prices.

The literature on institutional herding has been severely handicapped by the unavailability of appropriate data which should be both, high-frequent and investor-specific. Typically, the positions taken by institutions on the stock market are published infrequently, if at all. For example, for US mutual funds and certain other institutional investors, reports of holdings are available only on a quarterly basis, see, e.g., Choi and Sias (2009) and Wermers (1999). Walter and Weber (2006) analyze herding for German mutual funds at a semi-annual frequency. Kremer and Nautz (forthcoming) show that empirical herding measures can be severely affected by data frequency. Low-frequent trading data also impedes the analysis of the price impact of herding. Since there is no resolution on, say, intra-quarter covariances of trades and returns, it remains unclear whether institutions are reacting to or causing stock price movements.

The empirical literature proposes several approaches to ameliorate these data problems. For example, Venezia et al. (2011) employ investment transactions provided by a large bank in Israel that allow to explore the herding behavior of investors on a monthly basis. Barber et al. (2009) circumvent the problem of low data frequency by using anonymous transaction data instead of reported holdings.[1] Chen and Hong (2006) exploit daily data from

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[1] Since the data does not identify the trader, trades above a specific cutoff size are assumed to be institutional. According to Kremer and Nautz (forthcoming), evidence based on anonymous transaction data can lead to misleading conclusions.

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the Taiwan Stock Exchange that provides for each stock information about the fraction of shares held by institutional investors. Although the data is not investor-specific, the relation between daily overall institutional ownership changes, stock attributes and subsequent returns sheds new light on the trading behavior of institutional investors and the price impact of herding.

The current paper contributes to the empirical literature on herding by using daily investor-specific data that directly identify institutional transactions. Our analysis therefore overcomes the data problems inherent in previous studies and provides new evidence on the short-term herding behavior of financial institutions for a broad cross-section of stocks on the German stock market for the period from July 2006 to March 2009. Moreover, the availability of daily, investor-specific data enables us to perform a panel econometric analysis of the causes of herding and its consequences for the dynamics of stock prices.

Our results show that financial institutions do indeed herd within a day. Herding intensity depends on stock characteristics as well as on past returns and stock volatility. However, in contrast to theories of intentional herding, herding is more pronounced in larger and more liquid stocks. Results from panel regressions support that the observed herding is rather unintentional. In particular, we show that herding intensity depends on past volatility in an asymmetric way, i.e. rising stock volatility leads to increased sell herding while buy herding measures decrease. This finding could be explained by the widespread use of similar risk measures that drives correlated sell activity after a rise in volatility.

If herding drives prices away from fundamental values, destabilizing effects of herds should be reflected in subsequent return reversals, see, e.g., Choi and Sias (2009). Our results support a destabilizing impact of herding on stock prices. Results obtained from panel regressions indicate that the destabilization of stock prices is particularly strong in case of sell herds. If destabilizing sell herds are partly caused by similar market-sensitive risk management systems, our results on the causes and consequences of herding emphasize the importance of a macro-prudential view on financial regulation.

The remainder of the paper is structured as follows. Section 2 reviews the theories behind herding behavior and summarizes the empirical literature. Section 3 introduces the data and Section 4 discusses the herding measures. Sections 5 and 6 present the empirical analysis of the causes and consequences of herding. Section 7 concludes.

2. Theory and empirical literature

2.1. Intentional versus unintentional herding

The term herding is used to describe the tendency of institutions or individuals to behave similarly, thus acting like a herd. Herding behavior can be either intentional or unintentional, see Bikhchandani and Sharma (2001). Unintentional herding occurs when institutions are attracted to stocks with certain characteristics such as higher liquidity (see, e.g., Falkenstein (1996)) or when institutions rely on the same factors and information, leading them to arrive at similar conclusions regarding individual stocks (see, e.g., Hirshleifer et al. (1994)). Moreover, professionals may constitute a relatively homogenous group: they share a similar educational background and professional qualifications and tend to interpret informational signals similarly. A prominent example is the common reaction of financial institutions to similar risk measures.

Intentional herding is more sentiment-driven and involves imitating other market participants, resulting in simultaneous buying or selling of the same stocks regardless of prior beliefs or information sets. There are two major theoretical models that explain the rationale behind this behavior. According to e.g. see Bikhchandani et al. (1992), Banerjee (1992), Avery and Zemsky (1998) and Park and Sabourian (2011), rational traders copy the investment activity of other market participants because they infer (from observed trading behavior) that others have relevant information. The second explanation for herding behavior is derived from 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. Therefore, traders are uncertain about their decisions and follow the crowd. In contrast, in the case of unintentional herding, traders acknowledge public information as reliable. Yet, since they interpret it similarly, they all end up on the same side of the market. Therefore, both types of herding are linked to the uncertainty and availability of information.

2.2. Causes of herding

Distinguishing between different causes or types of herding behavior is crucial for regulatory purposes and for discovering whether herding leads to market inefficiency. However, identifying the type of herding is not an easy task because a large number of factors may influence an investment decision and because the motives behind a trade are not discernable. 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.

2.2.1. Size

Lakonishok et al. (1992) investigate herding within a quarterly time span using a sample of US equity funds. They segregate stocks by size because the market capitalization of firms usually reflects the quantity and quality of available information. Thus, one would expect higher levels of herding in trading small stocks to be 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) do find evidence of herding being more intense among small companies compared to large stocks. Recently, Choi and Sias (2009), and Venezia et al. (2011) confirm a greater extent of herding in small stocks. Following the literature, we measure firm size (*Size*) by the logarithm of the previous day's closing market capitalization of the specific stock.

2.2.2. Trading volume

A vast literature highlights the relation between information quality, market liquidity and information asymmetries. For example, 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.[2] We therefore use the trading volume (Vol_i) of a stock i as a proxy for information asymmetry. Intentional herding theory implies that lower trading volumes are associated with higher herding levels.

2.2.3. Feedback trading

As unintentional herding occurs due to simultaneous reaction to a common signal, a manifestation of this kind of herding is

[2] In the same vein, lower quality of information and lower market transparency may lead to higher herding levels in emerging markets compared to developed ones, see e.g. Voronkova and Bohl (2005).

Table 1
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, see Section 2.2. "–", "+" and "0" denotes a negative, positive and insignificant impact, respectively.

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 et al. (1992) and Sias (2004). The evidence on feedback trading to date is mixed. In contrast to Lakonishok et al. (1992), Grinblatt et al. (1995) document positive feedback strategies that contribute to herding. Wylie (2005) finds that UK funds herd out of stocks that have performed well in the past. Although correlated positive feedback trading may lead to unintentional herding, it could have a destabilizing impact on financial markets, see, e.g., De Long et al. (1990). In the empirical analysis, feedback trading is typically captured by lagged returns (r_i) of stock *i*.

2.2.4. Risk management systems and the volatility of returns

The impact of return volatility on empirical herding measures is particularly revealing. On the one hand, stock return volatility is often assumed to reflect the extent of disagreement among market participants and, thus, the degree of uncertainty in the market. Intentional herding models would therefore predict higher herding in stocks that experienced a higher degree of volatility. It is worth emphasizing that higher information uncertainty should induce intentional herding in a *symmetric* way, i.e., on both the buy and the sell side.

On the other hand, higher levels of herding in more volatile stocks might also be related to a widespread use of the same risk measures. VaR models or other volatility sensitive models commonly used for risk management purposes and regulatory requirements may induce common sell activity, see e.g. Persaud (2000). In particular, backward-looking risk measures – which form the basis for position limits and regulatory market risk capital – often force banks to close positions in volatile periods. In this case, we expect more unintentional herding in stocks with higher volatility of returns. IMF (2007) confirms this hypothesis by a simulation study which illustrates common sell activities in volatile periods by banks using similar risk models. However, in contrast to the case of intentional herding, the impact of volatility stirred by common risk management practices on unintentional herding should be *asymmetric*: only sell (not buy) herding should increase in response to high return volatility. In the empirical analysis return volatility (*Std*) shall be measured by the standard deviation of the past 250 daily stock returns, i.e. those observed over the trading days of the preceding year. This coincides with the minimum period according to Basel II market risk standards.[3]

Table 1 summarizes the theoretical predictions regarding the determinants of herding. Note that the role of stock return volatility, *Std*, may differ for buy and sell herding.

2.3. Consequences of herding

Institutional herds may induce price pressure and thus impact stock prices. This is not necessarily a bad thing. For example, unintentional herding can be an efficient outcome, if it results from the simultaneous reaction to fundamental values which speeds up price adjustment and makes the market more efficient, see Lakonishok et al. (1992). However, herding can lead to inefficient outcomes if not based on fundamentals. In this case, herding causes a destabilization of markets, with the potential to create, or at least contribute to, bubbles and crashes, see, e.g., Scharfstein and Stein (1990). A prominent example is unintentional herding due to positive feedback strategies that aggravate downward or upward pressures, see, e.g., De Long et al. (1990). Moreover, Daníelsson (2008) or Persaud (2000) emphasize the destabilizing effects of market sensitive risk regulation that forces common reaction on volatility and thus the endogeneity of risks. IMF (2007) demonstrate in a simulation exercise the destabilizing impact of return volatility if institutions employ similar risk models.

Scharfstein and Stein (1990) and Barberis and Schleifer (2003) suggest that if herding drives prices away from fundamentals, price movements should reverse subsequently. To this end, empirical analyses have been conducted to discover whether the impact of herding on prices continues or reverses in the future, where the latter is interpreted as destabilizing impact, see, e.g., Choi and Sias (2009). The empirical evidence on the consequences of herding is mixed. Using quarterly data, Lakonishok et al. (1992), Wermers (1999) or Sias (2004) do not find return reversals following herds. In contrast, more recent studies, including, e.g. Puckett and Yan (2008) and Brown et al. (2010) confirm herding-related return reversals using weekly data. In fact, 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 the actions of arbitrageurs. In Section 6, we provide new evidence from panel regressions on the relevance of herding-related return reversals using daily data.

3. Data

3.1. Description of the database

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 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]

[3] Very similar results are obtained using standard deviations based on the last 90 or 30 stock returns. For brevity, results are not presented but are available on request.

[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 they 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 designated sponsors for each stock are published at http://www.deutsche-boerse.com.

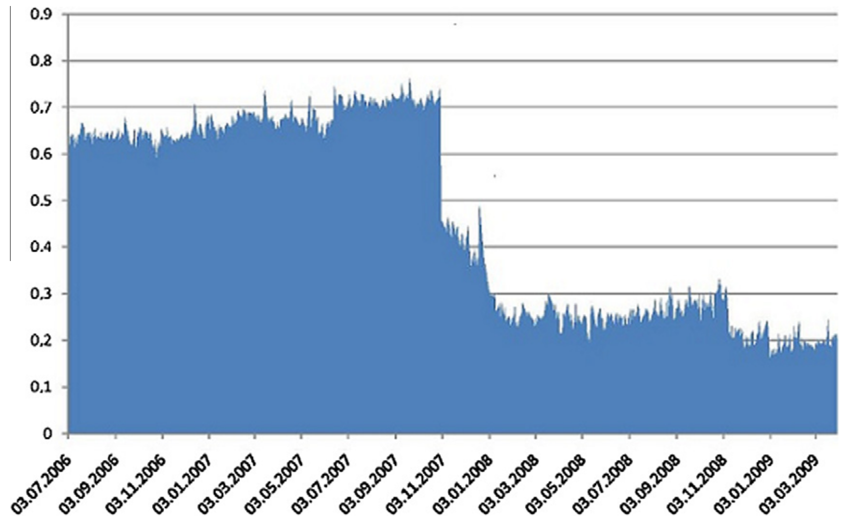

Fig. 1. Share of institutional investors in the trading volume. *Notes:* The figure shows the development of the share that institutions have in the trading volume averaged over DAX 30 stocks. *Source:* BaFin records and Datastream.

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) where stocks are selected according to the index compositions at the end of the observation period on March 31, 2009. These indices allow to investigate the trading behavior in small and large stocks. In line with the empirical literature we require that at least five institutions were active in the market at each day. This condition slightly reduces the sample size from 88,435 to 83,842 daily observations of stock-specific herding measures.

Using data from July 2006 to March 2009 (698 trading days), we cover market upturns as well as the recent market downturn. Therefore, the sample allows to investigate whether trading behavior has changed during the financial crises. Over this period, there are 1120 institutions performing proprietary transactions. Among those 1120 traders, 1044 trade on the DAX 30 stocks, 742 on the MDAX stocks and 512 on the SDAX stocks. For each institution, we compute the daily trade imbalance. Taking the average across all stocks, about 25 institutions trade each day which justifies the use of daily data. Institutional traders have an average daily market share of DAX 30 stocks of about 46%. Interestingly, the market share declined after the start of the recent financial crises, implying a retraction from trading business, see Fig. 1. In the period from 01 July 2006 until 08 August 2007 the proportion constituted 66%, shrinking to 32% after 09 August 2007. Table 5 in the appendix provides more detailed information on trading activities in the German stock market.

3.2. Most active traders

The theory of unintentional herding predicts higher herding levels among institutions that share the same investment style and professional qualifications, see Hirshleifer et al. (1994). 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). In contrast, the full sample of 1120 institutions is a very 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. This group of 30 traders contains the most professional traders in the German stock market which can be considered as peers. Any destabilizing impact found for this group would suggest a high potential threat to financial stability. In the following, we therefore focus the attention on the herding behavior of the 30 most active traders. The resulting subsample includes 68,963 observations.[5]

The sample of the 30 most active traders includes both, German and foreign institutions. German banks are all subject to the same regulatory regime and oversight by the financial authority. For these banks, the information contained in their annual reports confirm that they all use VaR models and implement regulatory or internal VaR limits. According to an analysis of risk management systems in the *IMF Global Financial Stability Report*, the regulatory framework and risk management systems of the foreign banks in the 'most active trader' sample can be expected to be similar, compare IMF (2007). Based on a survey of risk measurement and management practices disclosed in publicly available documents and through interviews with the banks, this shows that all major investment banks employ VaR models based on historical data as a market risk measure. The homogeneity regarding risk models becomes especially relevant when we investigate the causes of common sell activity in Section 5.

4. Do institutions herd?

4.1. The herding measure

Like most 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.[6]

[5] A subgroup of 30 traders ensures that enough traders are active in a specific stock on a specific day. For the sake of robustness, we created an additional subsample that only contains the most active German banks. In this case, the group size is increased to 40 to ensure that enough traders are active in a specific stock on a specific day which gives 69,257 observations. The empirical herding measures were not significantly affected by this choice, compare Tables 9 and 10 in the appendix.

[6] For sake of robustness, we also applied the herding measure introduced by Sias (2004) which is based on the correlation of the fraction of buyers across time. The results do not affect our main conclusions, see Table 11 in the appendix. A different concept of market-wide herding is proposed by Chiang and Zheng (2010) where herding is reflected in the cross-section correlation between returns of different firms.

Table 2
LSV herding measures: 30 most active traders.

Sample	All stocks				DAX 30			
	HM	*BHM*	*SHM*	Δ*BS*	*HM*	*BHM*	*SHM*	Δ*BS*
2006–2009	2.48	2.67	2.30	0.37	5.18	5.28	5.08	0.21
	(0.03)	(0.05)	(0.05)	(0.07)	(0.06)	(0.08)	(0.08)	(0.12)
Observations	68,963	35,806	33,130		20,853	10,692	10,154	
Pre-Crisis	2.93	3.55	2.15	1.41	5.84	6.26	5.35	0.91
	(0.05)	(0.07)	(0.08)	(0.11)	(0.08)	(0.12)	(0.12)	(0.17)
Observations	30,362	16,868	13,494		8,427	4546	3,881	
Crisis	2.14	1.87	2.41	−0.51	4.73	4.55	4.92	−0.35
	(0.05)	(0.07)	(0.07)	(0.10)	(0.08)	(0.12)	(0.12)	(0.16)
Observations	38,601	18,938	19,636		12,426	6,146	6,273	
Δ Crisis	0.79	1.68	−0.26		1.11	1.71	0.42	
	(0.07)	(0.10)	(0.11)		(0.12)	(0.17)	(0.18)	

Notes: LSV herding measures *HM*, *B*(*uy*)*HM* and *S*(*ell*)*HM* obtained for the 30 most active institutions calculated for all stocks (including DAX30, MDAX, and SDAX) and for DAX 30 only, see Eqs. (1)–(3). The minimum number of traders is 5. Herding measures are averaged across the different time periods and sub-groups of stocks. Δ*BS* and (Δ*Crisis*) report the differences between buy and sell herding and between the pre-crisis and the crisis period, respectively. Standard errors are given in parentheses. The "Pre-Crisis" period ends in 08/09/2007.

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.[7] 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 important variable is $\overline{br}_t$, i.e. the average of the buyer ratio over all stocks at time t. This variable accounts for an overall trend in the market at t.

The LSV herding statistic is given by

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

The first term captures the deviation of the buyer 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 $E_t[|br_{it} - \overline{br}_t|]$ is the expected value of the difference between the buyer ratio and period-average buyer ratio. Subtracting this term accounts for the possibility of observing more variation in the buyer 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.[8]

The empirical literature following Lakonishok et al. (1992) calculates the mean across all stocks and all periods for obtaining 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 $\overline{HM}$, the stronger the herding. For example, $\overline{HM} = 2\%$ indicates that out of every 100 transactions, 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 $\overline{br}_t$.

HM_{it} measures herding without regard to the direction of the trades (buy or sell). Following Grinblatt et al. (1995) and Wermers (1999), we distinguish between "buy herding" BHM_{it} and "sell herding" SHM_{it}, to discover whether institutions buy or sell a stock i in herds, where

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

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

Note that $br_{it} = \overline{br}_t$ 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. BHM_{it} and SHM_{it} capture asymmetries in institutions' behavior when buying or selling, where $\Delta BS = \overline{BHM} - \overline{SHM}$, see Table 2. The separate measurement of herding *into* stocks and *out* of stocks will be important for the analysis of the causes of herding performed in Section 5.

4.2. Herding of institutions in the German stock market

Table 2 shows the daily LSV herding measures for the 30 most active traders in the German stock market calculated for different stock indices and time periods. The mean daily herding measure across all stocks (covering DAX30, MDAX, and SDAX) is 2.48%.[9] Considering only DAX 30 stocks, the herding measure rises to 5.18%, a high level of herding compared to previous findings.[10] In fact, for the medium and small stocks contained in the MDAX and SDAX indices, herding measures are significantly smaller, see Table 7 in the appendix. This result does not support the theory of *intentional* herding, which predicts higher herding levels in small and less liquid stocks, i.e. in stocks with less information availability and asymmetry. This strongly suggests that the observed herding behavior is mainly of the *unintentional* type. Following, e.g. Puckett and Yan (2008) and Lakonishok et al. (1992), this conclusion can be confirmed using a portfolio sorting approach, see Table 8 in the appendix.

Note that herding measures are typically higher in the pre-crisis period. The only exception refers to sell herding intensities calculated on the basis of all stocks, where sell herding in the crisis exceeds the pre-crisis value by only 0.26. This seemingly counterintuitive finding is probably implied by the construction of empirical

[7] 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.

[8] Following previous studies, e.g., Wermers (1999), HM_{it} is computed only if at least five traders are active in i at time t. In our sample, the resulting loss of observations is not an issue, see Section 3. Table 5 in the appendix shows that even for the small stocks of the SDAX, on average 10.78 institutions are active each day in each stock. We experimented with different minimum numbers of traders but results are robust with respect to this assumptions. For brevity, these results are not included in the paper but are available on request.

[9] We also calculated the median-based herding measures to check for robustness. The results shown in Table 6 indicate that all conclusions remain valid for the alternative herding measure.

[10] Similar results are found for the sample of the 40 most active German banks, compare Tables 9 and 10 in the appendix. As expected, Table 2 shows higher herding measures for the 30 most active traders compared to the findings of Kremer and Nautz (forthcoming) obtained for all 1120 institutions. Results based on the Sias herding measure do not affect our conclusions, see Table 11 in the appendix.

Table 3
Causes of herding – results from panel estimation.

	HM_{it}	BHM_{it}	SHM_{it}
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)
$\lvert r_{i,t-1}\rvert$	−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)
$Dummy^b_{it}$		0.0156***	
		(0.0011)	
$Dummy^s_{it}$			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	$\chi^2 = 3383.14$	$\chi^2 = 4924.52$	$\chi^2 = 1290.95$
	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0000)$
Sargan − Hansen	$\chi^2 = 10.343$	$\chi^2 = 16.422$	$\chi^2 = 17.536$
	$(Prob > \chi^2 = 0.0350)$	$(Prob > \chi^2 = 0.0353)$	$(Prob > \chi^2 = 0.0036)$
Observations	65,846	34,130	31,691

Notes: Estimation results from Eqs. (4)–(6). Herding measures 30 most active traders are regressed on $Size_{i,t-1}$, Vol_{it}, $|r_{i,t-1}|$ and Std_{it}. The buy and sell herding measures BHM_{it} and SHM_{it} use $r_{i,t-1}$ instead of $|r_{i,t-1}|$. $Size_{i,t-1}$ measures market capitalization, Vol_{it} trading volume, $r_{i,t-1}$ the daily return. Std_{it} is the standard deviation of past 250 daily stock returns. $Dummy^b_{it}$ ($Dummy^s_{it}$) are dummies indicating whether buy or sell herding occurred also on the previous day $t-1$. Significance at 5%, and 10% is represented as $**$, and $*$ respectively. Heteroscedasticity-robust standard errors according to Stock and Watson (2008) are given in parentheses. 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. Compared to Table 2, the number of observations is slightly reduced due to missing data for some of the control variables.
*** Significance at 1%.

herding measures which only account for excess trading over the overall trend, compare (1). This may explain why measured sell herding activities of institutions are low even in the crisis period.

5. Causes of herding: Results from panel regressions

5.1. Empirical determinants of herding behavior

Let us now investigate the potential causes of herding behavior in a panel econometric framework. In accordance with Venezia et al. (2011), we examine the relation between institutional herding and its determinants using 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 daily LSV herding measure of the 30 most active traders and i is a stock contained in one of the indices SDAX, MDAX, or DAX30. $Size_{i,t-1}$ 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 $t-2$. Note that we include the absolute returns because HM_{it} does not discriminate between the buy and sell sides. Std_{it} denotes volatility, measured as the standard deviation of the past 250 daily stock returns. α_i are stock-specific effects and γ_t are time dummies.[11]

Let us first look at the results for the regression with the unsigned herding measure HM, which are presented 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 found in Section 4.2 can be explained by these stocks' higher liquidity and is not driven by market capitalization. Note, however, that the size effect might already be captured by the fixed effects in the regression, since market capitalization changes only slightly over time.[12] Higher trading volume should be related to lower information asymmetry and higher information quality implying that the degree of *intentional* herding should be low. Following Falkenstein (1996), institutions are attracted to stocks with higher trading volume. Therefore, the positive coefficient of *VOL* could be an indication of *unintentional* herding.

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 intentional herding. Venezia et al. (2011) estimate a negative relation between herding *HM* and risk, i.e., the less risky the stock the more herding occurs. They explain their finding with Falkenstein's (1996) theory, arguing that herding appears as investors generally are attracted to less risky stocks. In the following, we will estimate the influence of volatility on buy and sell herding separately which shall lead us to an alternative explanation.

5.2. Buy and sell herding

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

[11] 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.

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

The only exception refers to the absolute return $|r|$ which is replaced by the signed return r because the direction of the recent price movement will affect whether momentum investors herd on the buy or the sell side:

$$BHM_{it} = a^b + b^b Size_{i,t-1} + c^b Vol_{it} + d^b r_{i,t-1} + e^b Std_{it} + e^b Dummy^b_{it} + \alpha^b_i + \gamma^b_t + \epsilon^b_{it} \tag{5}$$

$$SHM_{it} = a^s + b^s Size_{i,t-1} + c^s Vol_{it} + d^s r_{i,t-1} + e^s Std_{it} + e^s Dummy^s_{it} + \alpha^s_i + \gamma^s_t + \epsilon^s_{it} \tag{6}$$

The equations further include a dummy variable $Dummy^b_{it}$ ($Dummy^s_{it}$) which equals one if buy herding (sell herding) also occurred on the previous day $t-1$ and is zero otherwise.[13]

The results for the fixed effects panel regressions for 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.

It is important to note that the signs of the estimated *Std* coefficients differ between the buy and sell herding regression. In case of sell-side herding, *Std* has a significant positive impact. Thus, the higher the volatility of a stock, the more herding occurs on the sell side. In contrast, in case of buy-side herding, the impact of *Std* is significantly negative. This asymmetric effect is not compatible with the theory of intentional herding where return volatility should affect buy and sell herding in the same way. Apparently, institutions share a preference for selling (buying) stocks that have shown a high (low) volatility. This is a clear indication of unintentional herding that might be a result of common risk management practices, see Daníelsson (2008).

The estimated impact of lagged returns r is statistically significant for buy and sell herding regressions. Again, 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), and 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.[14]

5.3. Results for less active traders

So far, the focus of our empirical analysis was on the herding behavior of highly active traders. This important group of traders is rather homogenous having similar professional qualifications and investment styles. In particular, we argued that the asymmetric impact of return volatility on their herding intensity presented in Table 3 can be partly explained by bank regulation and similar risk management techniques that force banks to close positions in volatile periods. In order to provide more evidence on this argument, this section considers the herding behavior for the large and heterogenous group of less active institutions. In fact, the majority of these 1090 institutions is only rarely active in the stock market and mainly consists of "non-trading book institutions", where trading book activity does not exceed specific thresholds.[15] These rather non-active institutions are not required to apply provisions of the Banking Act concerning trading book business. In particular, capital provisions for market risk positions are not applicable. As a consequence, for less-active traders, the asymmetric response of herding measures to return volatility should be less pronounced.

In order to shed more light on the role of volatility and risk management on herding, we re-estimated Eqs. (5) and (6) for herding measures BHM_{it} and SHM_{it} derived for the group of less active financial institutions. The detailed results are reported in Table 12 in the appendix. Our findings obtained for the herding behavior of less active institutions support the hypothesis on the role of risk management practices for the positive impact of volatility on sell herding found for highly active traders. In contrast to evidence found for highly active traders, the estimation results imply that return volatility *Std* does not increase the sell herding intensity of less active traders. In fact, the estimated coefficient of Std_{it} (-0.0007) is negatively signed and both, economically and statistically insignificant.

6. The consequences of herding for stock prices

Let us now investigate the consequences of the herding behavior established in the previous sections. According to e.g. Sias (2004), significant herding measures are not particularly problematic if they only reflect the incorporation of fundamental information into asset prices. In this case, a positive (negative) correlation of buy (sell) herding and subsequent returns should continue over time. In contrast, if herding drives stock prices away from fundamental values, one would expect to observe significant return reversals.

For $n = 1, 2, \ldots, 20$ trading days, let $r_{i,t,t+n}$ denote the cumulative return of stock i from t to $t+n$. To investigate the impact of herding on subsequent returns, we estimate the following fixed effects panel regression models for each n:

$$r_{i,t,t+n} = a^n + b^n BHM_{it} + c^n SHM_{it} + d^n Size_{it} + e^n BM_{it} + f^n r_{i,t,t-5} + g^n r_{i,t,t-250} + h^n Std_{it} + i^n RMRF_t + j^n RINT_t + \alpha^n_i + \gamma^n_t + \epsilon^n_{it}, \tag{7}$$

Following e.g. Puckett and Yan (2008) and Barber et al. (2009), Eq. (7) contains a battery of control variables. Specifically, we include:

- $Size_{it}$, the logarithm of closing market capitalization of stock i
- BM_{it}, the book-to-market ratio of stock i
- $r_{i,t,t-5}$, the past cumulative return of stock i
- $r_{i,t,t-250}$, the past cumulative return to control for momentum in returns
- Std_{it}, the standard deviation of the past 250 daily stock returns
- the excess market return $RMRF_t$ calculated as difference between daily returns of the Composite DAX (CDAX), covering all stocks in the general and prime standard, and the risk free rate proxied by the 3-month money market rate
- $RINT_t$, the international market return factor measured as daily return of the MSCI World Index

The regressions further include stock-specific effects α_i and time dummies γ_t. Note that we estimated several alternative specifications to ensure the robustness of our results. For example,

[13] These dummies partly account for persistence of herding on either the buy or sell side, see also the results from the Sias measure in Table 11. We include dummy variables rather than the lagged endogenous variable to avoid too many missing observations. Note that the exclusion of those dummies would not impact our main results.

[14] We also experimented with lagged returns up to five trading days, $r_{i,t-2}, \ldots, r_{i,t-5}$ and cumulative return measures but the estimation results do not change in a significant way. These results are not presented but are available on request.

[15] For an exact definition, see Section 2 par. 11 in connection with Section 1a of the German Banking Act.

Table 4
The price impact of herding – results from a panel regression.

	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
BHM_{it}	0.198	0.653***	0.897***	0.987***	1.398***	1.981***
	(0.161)	(0.238)	(0.322)	(0.377)	(0.512)	(0.698)
SHM_{it}	−0.503***	−0.915**	−0.697**	−0.986**	0.620	0.696
	(0.176)	(0.256)	(0.303)	(0.493)	(0.601)	(0.811)

Notes: Results from panel regressions of cumulative stock returns on measures of buy and sell herding, see Eq. (7). See also Tables 3 and 13 for further explanation. Significance at 10% is represented as *. Standard errors are given in parentheses. Results for the complete set of regressors are displayed in Table 13 in the appendix.
** Significance at 5%.
*** Significance at 1%.

estimations without time dummies or with alternative lagged return specifications or volatility measures lead to very similar results which are not presented but are available upon request. We estimate the equations with GMM to avoid endogeneity problems using lagged variables as instruments. However, due to the large T, the endogeneity bias is negligible and results are consistent across estimation methods.[16]

Table 4 summarizes the main estimation results for a representative set of cumulative returns.[17] The results show that buy and sell herding affect cumulative returns differently. On the one hand, Table 4 shows that BHM_{it} significantly increases cumulative returns over the complete time horizon. Accordingly, there is no return reversal and, thus, no indication of a destabilization of stock prices in the aftermath of an institutional buy herd. The return continuation after buy herding suggests that correlated buy activities of institutional traders are mainly driven by new information about fundamentals. On the other hand, however, sell herds (SHM_{it}) do lead to significant return reversals. While cumulative returns significantly decrease in the short-term, coefficients loose their significance after 5 days and eventually even change their sign.[18] The resulting reversal of returns indicates that sell herds push prices below their fundamental values, compare Chen and Hong (2006). In accordance with the impact of volatility on sell herding estimated in the previous section, the destabilizing effect of sell herds may be explained by common sell activities of institutional traders induced by volatility sensitive models used for risk management, see Daníelsson (2008) and IMF (2007).

7. Conclusions

This paper contributes to the empirical literature on herding by using higher-frequency investor-level data that directly identify institutional transactions, thus overcoming data problems faced by earlier work. We explore the causes and the consequences of herding by financial institutions for a broad cross-section of German stocks over the period from July 2006 to March 2009.

Our results provide new evidence on the short-term herding behavior of financial institutions. We show that herding is more pronounced in the DAX30, the index of the 30 largest and most liquid stocks, than in the less liquid indices MDAX and SDAX. Since small capitalization stocks are less vulnerable to herding behavior, the observed herding cannot be explained with insufficient information availability or information asymmetry. Apparently, herding behavior is more of the unintentional type, i.e. driven by widespread identical reaction to public information and signals, see Bikhchandani and Sharma (2001).

[16] For brevity, OLS results are not presented. We accounted for heteroscedasticity and autocorrelation in the error terms by using robust standard errors, see Stock and Watson (2008). The lower part of Table 13 in the appendix presents test statistics and p-values of diagnostic tests.

[17] More detailed results are presented in the appendix, see Table 13. Estimated coefficients of control variables are consistent with earlier evidence. For example, 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.

[18] More precisely, coefficient estimates start to decrease for $n = 6$, become insignificant at $n = 7$ and change the sign with $n = 9$. Results are not reported for brevity but are available on request.

Table 5
Trading intensity and market share of institutions.

	All	DAX 30	MDAX	SDAX
Average daily number of traders active				
2006–2009	25.14	50.79	23.41	10.78
Pre-Crisis	31.96	65.26	28.80	13.10
Crisis	20.80	41.01	20.00	9.34
Average daily market share in percent				
2006–2009	51.00	45.97	51.00	54.30
Pre-Crisis	70.34	65.91	75.33	68.71
Crisis	39.45	32.46	37.43	45.82

Notes: The upper panel reports the average across stocks and time of institutions active in the corresponding index of the German stock market. The numbers are computed according to the daily trade imbalance of the institutions. The lower panel shows for each stock index the average share of the trading volume due to institutions. "Pre-Crisis" indicates the period before 08/09/2007 and "Crisis" the period after 08/09/07.

Table 6
Median-based LSV herding measures: 30 most active traders.

	All stocks				DAX 30			
Sample	*HM*	*BHM*	*SHM*	*ΔBS*	*HM*	*BHM*	*SHM*	*ΔBS*
2006–2009	1.07	1.36	0.76	0.60	4.11	4.25	3.94	0.32
	(0.05)	(0.06)	(0.07)	(0.09)	(0.08)	(0.09)	(0.10)	(0.15)
Observations	68,963	35,806	33,130		20,853	10,692	10,154	
Pre-Crisis	1.62	2.28	0.81	1.45	4.77	5.11	4.37	0.74
	(0.07)	(0.09)	(0.10)	(0.11)	(0.11)	(0.11)	(0.14)	(0.19)
Observations	30,362	16,868	13,494		8,427	4546	3,881	
Crisis	0.61	0.58	0.73	−0.15	3.47	3.46	3.47	−0.01
	(0.06)	(0.08)	(0.10)	(0.13)	(0.11)	(0.10)	(0.15)	(0.23)
Observations	38,601	18,938	19,636		12,426	6,146	6,273	
Δ Crisis	1.03	1.70	0.08		1.30	1.65	0.89	
	(0.07)	(0.13)	(0.15)		(0.16)	(0.22)	(0.22)	

Notes: The table displays the median of the herding measure for the different time periods and sub-groups of stocks, compare Table 2 for standard mean-based LSV measures. ΔBS and ($\Delta Crisis$) report the differences between buy and sell herding and between the pre-crisis and the crisis period, respectively. Standard errors are given in parentheses. The "Pre-Crisis" period ends in 08/09/2007. See Table 2 for further information.

Table 7
LSV herding measures of 30 most active traders: Small stocks.

	MDAX		SDAX	
Sample	*HM*	DAX-MDAX	*HM*	DAX-SDAX
2006–2009	1.18	4.11	1.59	3.70
	(0.05)	(0.08)	(0.09)	(0.11)
Observations	31,668		16,442	
Pre-Crisis	1.78	4.06	1.85	3.99
	(0.07)	(0.12)	(0.12)	(0.15)
Observations	12,749		9186	
Crisis	0.76	3.96	1.25	3.47
	(0.07)	(0.11)	(0.14)	(0.15)
Observations	18,919		7256	

Notes: Mean values of *HM* for MDAX and SDAX stocks for the 30 most active institutions. DAX-MDAX (DAX-SDAX) denotes the differences between the LSV measures of DAX and MDAX (SDAX). Positive values and standard errors indicate that herding intensity is significantly higher in the DAX30. See Table 2 for further information.

Table 8
LSV herding and size-effects: Results from a portfolio analysis.

HM by size					
Q1 (small)	Q2	Q3	Q4	Q5 (large)	Q5–Q1
0.91	0.95	1.93	1.66	4.96	4.05
(0.14)	(0.09)	(0.07)	(0.07)	(0.06)	(0.14)
HM by trading volume					
Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5–Q1
0.35	0.80	1.81	1.89	5.18	4.82
(0.13)	(0.10)	(0.08)	(0.07)	(0.07)	(0.35)

Notes: LSV measures for stocks sorted in quintiles according to their market capitalization (*first panel*) and their trading volume (*second panel*). Standard errors are given in parentheses. According to Q5–Q1, herding in large and highly-traded stocks is most pronounced.

Table 9
LSV herding measures: 40 most active German banks.

	All stocks				DAX 30			
Sample	*HM*	*BHM*	*SHM*	ΔBS	*HM*	*BHM*	*SHM*	ΔBS
2006–2009	2.16	2.11	2.31	−0.20	5.13	5.05	5.30	−0.25
	(0.03)	(0.05)	(0.05)	(0.13)	(0.05)	(0.08)	(0.08)	(0.16)
Observations	69,274	34,573	34,694		20,897	10,132	10,764	
Pre-Crisis	1.96	2.07	1.85	0.22	4.78	4.65	4.86	−0.21
	(0.05)	(0.04)	(0.08)	(0.11)	(0.08)	(0.09)	(0.12)	(0.18)
Observations	27,635	13,728	13,907		8,425	4,044	4,381	
Crisis	2.39	2.13	2.45	−0.32	5.37	5.31	5.48	−0.17
	(0.04)	(0.07)	(0.07)	(0.10)	(0.04)	(0.12)	(0.10)	(0.15)
Observations	41,639	20,845	20,787		12,472	6,088	6,383	
ΔCrisis	−0.43	−0.06	−0.60		−0.59	−0.66	−0.62	
	(0.15)	(0.14)	(0.14)		(0.12)	(0.17)	(0.18)	

Notes: LSV herding measures *HM*, *B*(*uy*)*HM* and *S*(*ell*)*HM* obtained for the 40 most active German institutions (compare Table 1) calculated for all stocks (including DAX30, MDAX, and SDAX) and for DAX 30 only. Herding measures are averaged across the different time periods and sub-groups of stocks. ΔBS and (ΔCrisis) report the differences between buy and sell herding and between the pre-crisis and the crisis period, respectively. Standard errors are given in parentheses. See Table 2 for further information.

Table 10
LSV herding measures of 40 most active German banks: Small stocks.

	MDAX		SDAX	
Sample	*HM*	DAX-MDAX	*HM*	DAX-SDAX
2006–2009	1.22	3.91	0.22	4.91
	(0.05)	(0.08)	(0.08)	(0.08)
Observations	31,630		16,747	
Pre-Crisis	1.25	3.52	0.14	4,64
	(0.07)	(0.09)	(0.12)	(0.08)
Observations	12,072		7138	
Crisis	1.21	4.17	0.50	4.87
	(0.07)	(0.10)	(0.11)	(0.09)
Observations	19,558		9609	

Notes: Mean values of *HM* for MDAX and SDAX stocks for the 40 most active German institutions. DAX-MDAX (DAX-SDAX) denotes the differences between the LSV measures of DAX and MDAX (SDAX). Positive values and standard errors confirm that herding intensity is significantly higher in the DAX30. See Table 2 for further information.

A panel econometric analysis provides further evidence on the causes of herding. In particular, our estimation results show that herding intensity depends on past volatility in an asymmetric way, i.e. rising stock volatility leads to increased sell herding while buy herding measures decrease. This result is not compatible with the symmetric impact predicted by standard herding theory, compare Park and Sabourian (2011). A possible explanation for the asymmetric effect of volatility on herding is that it is mainly unintentional and driven by the common reaction to standard risk measures that force regulated traders to sell high-volatility stocks and to buy those with low volatility. This interpretation is supported by the fact that the asymmetric volatility effect cannot be found for the herding behavior of small and less active traders where, for

Table 11
Results from the Sias herding measure: 30 most active traders.

	Average correlation	Partitioned correlation	
		Follow own trades	Follow trades of others
2006–2009	16.42	11.40	5.02
	(0.34)	(0.27)	(0.26)
Pre-Crisis	19.61	12.01	7.60
	(0.57)	(0.40)	(0.24)
Crisis	14.25	10.98	3.27
	(0.52)	(0.38)	(0.23)
Buy herding			
2006–2009	6.23	4.35	1.88
	(0.23)	(0.14)	(0.15)
Pre-Crisis	7.65	4.74	2.91
	(0.37)	(0.23)	(0.15)
Crisis	5.27	4.09	1.18
	(0.35)	(0.19)	(0.15)
Sell herding			
2006–2009	10.19	7.06	3.13
	(0.24)	(0.20)	(0.12)
Pre-Crisis	11.96	7.26	4,70
	(0.33)	(0.29)	(0.12)
Crisis	8.98	6.90	2.08
	(0.35)	(0.28)	(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 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 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. "Pre-Crisis" indicates the period before 08/09/2007 and "Crisis" the period after 08/09/2007.

Table 12
Causes of herding: Results from panel regressions for less active traders.

	HM_{it}	BHM_{it}	SHM_{it}
Regressors			
$Size_{i,t-1}$	-0.0047^{***}	-0.0173^{***}	0.0089^{***}
	(0.0015)	(0.0019)	(0.0034)
Vol_{it}	0.0131^{***}	0.0210^{***}	0.0080^{***}
	(0.0007)	(0.0018)	(0.0033)
$\lvert r_{i,t-1}\rvert$	−0.0001		
	(0.0002)		
$r_{i,t-1}$		−0.0001	−0.0000
		(0.0002)	(0.0002)
Std_{it}	-0.0035^{***}	-0.0055^{*}	−0.0007
	(0.0008)	(0.0033)	(0.0016)
$Dummy^{b}_{it}$		0.0192^{***}	
		(0.0011)	
$Dummy^{s}_{it}$			0.0142^{***}
			(0.0011)
Diagnostics			
Wooldridge	$F = 2.105$	$F = 2.152$	$F = 0.153$
	$(Prob > F = 0.1492)$	$(Prob > F = 0.1449)$	$(Prob > F = 0.6964)$
Cook − Weisberg	$\chi^2 = 10392.26$	$\chi^2 = 5244.68$	$\chi^2 = 3888.83$
	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0000)$
Sargan − Hansen	$\chi^2 = 15.057$	$\chi^2 = 75.475$	$\chi^2 = 11.030$
	$(Prob > \chi^2 = 0.0046)$	$(Prob > \chi^2 = 0.0000)$	$(Prob > \chi^2 = 0.0508)$
Observations	67,709	31,026	31,474

Notes: Herding measures for the subgroup of 1090 less active traders are regressed on variables $Size_{i,t-1}$, Vol_{it}, $\lvert r_{i,t-1}\rvert$ and Std_{it}. Buy and sell herding measures BHM_{it} and SHM_{it} depend on the signed return $r_{i,t-1}$. See Table 3 for further explanation.

Table 13
The price impact of herding – complete set of results.

	$r_{i,t,t+1}$	$r_{i,t,t+2}$	$r_{i,t,t+3}$	$r_{i,t,t+5}$	$r_{i,t,t+10}$	$r_{i,t,t+20}$
Regressors						
BHM_{it}	*0.198*	0.653***	0.897***	0.987***	1.398***	1.981***
	(0.161)	(0.238)	(0.322)	(0.377)	(0.512)	(0.698)
SHM_{it}	−0.503***	−0.915***	−0.697**	−0.986**	0.620	0.696
	(0.176)	(0.256)	(0.303)	(0.493)	(0.601)	(0.811)
$Size_{it}$	−0.314***	−0.523***	−0.761***	−1.177***	−2.410***	−3.172***
	(0.051)	(0.077)	(0.095)	(0.122)	(0.163)	(0.155)
BM_{it}	0.082**	0.250***	0.438***	1.010***	1.477***	2. 025***
	(0.033)	(0.076)	(0.053)	(0.079)	(0.109)	(0.161)
Vol_{it}	0.043*	0.096***	0.128***	0.101**	0.085**	0.092
	(0.025)	(0.020)	(0.027)	(0.045)	(0.048)	(0.068)
$r_{i,t,t-5}$	−0.017***	−0.045***	−0.066***	−0.083***	−0.026***	−0.016
	(0.003)	(0.05)	(0.006)	(0.008)	(0.010)	(0.014)
Std_{it}	−0.0915***	−0.310***	−0.553***	−0.971***	−1.962***	−4.166***
	(0.021)	(0.031)	(0.038)	(0.049)	(0.066)	(0.096)
$RMRF_t$	0.050***	0.012	0.013	−0.144***	−0.162***	−0. 081**
	(0.007)	(0.011)	(0.013)	(0.014)	(0.023)	(0.033)
$r_{i,t,t-250}$	*0.003*	*0.013*	0.027**	0.039**	0.098***	0.165***
	(0.007)	(0.109)	(0.014)	(0.017)	(0.024)	(0.032)
r_int_t	0.858***	1.115***	1.032***	1.225***	1.101***	1.025***
	(0.006)	(0.014)	(0.125)	(0.016)	(0.024)	(0.036)
Diagnostics						
Wool.	$F = 14.92$	$F = 162.91$	$F = 743.34$	$F = 78.73$	$F = 249.21$	$F = 124.18$
	$(P > F = 0.00)$	$(P > F = 0.00)$	$(P > F = 0.00)$	$(P > F = 0.00)$	$(P > F = 0.00)$	$(P > F = 0.00)$
C.–W.	$\chi^2 = 10025.8$	$\chi^2 = 12966$	$\chi^2 = 11202$	$\chi^2 = 12142$	$\chi^2 = 13432$	$\chi^2 = 17319$
	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.00)$
S.–H.	$\chi^2 = 28.90$	$\chi^2 = 19.43$	$\chi^2 = 9.83$	$\chi^2 = 14.23$	$\chi^2 = 31.32$	$\chi^2 = 34.27$
	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.01)$	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.00)$	$(P > \chi^2 = 0.00)$

Notes: Results for the complete set of regressors for regressions of future stock returns on institutional herding, see Eq. (7). 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}, $r_{i,t,t-5}$, $r_{i,t,t-250}$, Std_{it}, $RMRF_t$ and r_int_t. 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 and Section 6.1. for more explanation.
* Significance at 10%.
** Significance at 5%.
*** Significance at 1%.

example, capital provisions for market risk positions do often not apply.

However, even unintentional herding may impede the efficiency of financial markets. In fact, we find that sell-side herding of active traders contributes to the short-term destabilization of stock prices, as indicated by subsequent return reversals. In accordance with e.g. IMF (2007) and Daníelsson (2008), our results suggest that the common use of VaR models and similar standardized volatility-sensitive risk measures reduces the diversity of decision rules, resulting in herding behavior by banks, with potentially 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 risk.

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Appendix A

See Tables 5–13.

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