The impact of information risk and market stress on institutional herding

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Abstract

This paper sheds new light on the impact of information risk and market stress on herding of institutional traders from both, a theoretical and an empirical perspective. Using numerical simulations of a herd model, we derive two new theory-based predictions. First, we show that buy and sell herding intensity should increase with information risk. Second, market stress should affect herding asymmetrically: while sell herding should increase during crisis periods, buy herding intensity should decrease. We test these predictions empirically using high-frequent, investor-specific trading data of all institutional investors in the German stock market. The evidence provides strong support for an increasing effect of information risk on herding intensity on an intra-day basis. In contrast to the simulation results, however, we do not find an asymmetric effect of market stress on herding intensity: both, sell and buy herding increased during the 2007 European financial crisis.

Keywords: Herd Behavior, Institutional Trading, Correlated Trading, Model Simulation

JEL classification: G11, G24, C23

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1 Introduction

Herd behavior among investors is often viewed as a significant threat for the functioning of financial markets. The distorting effects of herding on financial markets range from informational inefficiency to increased stock price volatility, or even bubbles and crashes. Given these potentially severe adverse effects of herd behavior on financial markets, this paper sheds more light on two determinants of herding intensity. First, while it is generally understood that herd behavior has the potential to *create* times of market stress, it is less clear whether the reverse relationship holds.[1] Therefore, we investigate whether increased market stress provides breeding ground for herd behavior, thereby creating vicious cycles of economic downturns and high volatility regimes. Second, herding theory emphasizes the role of asymmetric information for the possibility of herd behavior. In herd models, the degree of asymmetric information is reflected in information risk, defined as the probability of trading with a counterpart who holds private information about the asset, see Easley et al. (1996). Our second focus is, therefore, the analysis of the impact of information risk on herding intensity.

The theoretical literature on the causes and consequences of herd behavior was initiated by the seminal work of Bikhchandani et al. (1992) and Banerjee (1992).[2] Their concepts were put into a financial market context by Avery and Zemsky (1998). However, herding behavior in their model can hardly produce strong and persistent stock price movements, compare e.g. Chamley (2004). Advancing on Avery and Zemsky (1998), Park and Sabourian (2011) not only derive precise conditions under which herd behavior may occur, but also show that herding is a relevant phenomenon in modern financial markets.

[1] While Chiang and Zheng (2010) and Christie and Huang (1995) confirm that herding increases during times of market stress, Kremer and Nautz (2013a,b) find that herding in the German stock market even slightly decreased during the recent financial crisis. Similar results are provided by Hwang and Salmon (2004) for herding intensity during the Asian and the Russian crisis in the nineties.

[2] For comprehensive surveys of the herding literature, see e.g. Chamley (2004), Hirshleifer and Hong Teoh (2003) and Vives (2008).

In accordance with the empirical literature, we are particularly interested in *average* herding intensity observed in a heterogeneous stock market. However, herding models are not designed to provide analytical results about average herding intensity for a cross-section of stocks. As a consequence, the theoretical and empirical herding literature are only loosely connected. Typically, hypotheses tested empirically are intuitive but they are not rigorously derived from a particular herd model. For example, several empirical studies investigating the size effect of herding are based on the plausible but unproven hypothesis that herding intensity should be the lower the smaller the quantity and quality of available information, see e.g. Lakonishok et al. (1992), Wermers (1999), and Sias (2004). In the same vein, herding intensity is linked to the stage of the development of the financial market, see e.g. Walter and Weber (2006).

Focusing on the role of market stress and information risk on herding intensity, we try to fill this gap and derive theory-based predictions implied by numerical simulations of the Park and Sabourian (2011) herd model. The model simulation – based on a broad range of parameterizations generating about 380 million trades to analyze – yields two testable hypotheses: First, an increase in information risk should result in an increase of both, buy and sell herding intensity. And second, increased market stress should have an asymmetric effect on herding intensity - it should cause a decrease in buy herding intensity and an increase in sell herding intensity. To the best of our knowledge, these findings are the first theory-founded comparative static results for herding intensity in a stock market.

In the empirical part of the paper, both hypotheses are tested using an intra-day, investor-specific data set provided by the German Federal Financial Supervisory Authority (BaFin). The data include all real-time transactions in the major German stock index DAX 30 carried out by banks and financial services institutions.[3] The

[3] This data set has already been used by two companion papers. Kremer and Nautz (2013b) demonstrate that empirical herding measures are affected by both, the identification of traders and the underlying data frequency. Kremer and Nautz (2013a) regress daily herding measures on e.g. size, volatility and other stock characteristics to analyze the causes of herding.

data are chosen to be *intra-day* since private information in financial markets is fast moving and, as a consequence, the informational advantage from private signals can only be exploited for short time horizons. [4] Measuring herding at lower frequencies may bias the results because new information might have reached the market in the meantime, establishing a new context for investor behavior. The data are chosen to be *investor-specific* as we need to directly identify transactions by each trader in order to determine whether an investor is herding, i.e. whether she follows the observed actions of other traders. The empirical herding literature is often hampered by the availability of data having both characteristics. Typically, empirical studies have to rely on either investor-specific but low-frequent data, or on high-frequent but anonymous transaction data, compare Wermers (1999), Barber et al. (2009) or Zhou and Lai (2009).[5]

Following the herding literature, we are particularly interested in the herding behavior of institutional investors because they can be seen as informed traders, who - from a model perspective - are the only traders who can engage in herd behavior. Moreover, institutional investors are the predominant class in the stock market with the power to move the market and impact prices, particularly if they herd. The sample period runs from July 2006 to March 2009 which allows us to measure herding before and after the outbreak of the financial crisis. We employ the dynamic herding measure proposed by Sias (2004) which is particularly appropriate for the analysis of high-frequent data. Interestingly, the Sias measure has not been applied to intra-day data before. The Sias measure also exploits the second feature of our data: having access to investor-specific information, it allows to differentiate between traders that indeed follow predecessors and traders that simply follow themselves, for example, because they split their trades.

In accordance with Hypothesis 1, our empirical results show that herding intensity increases with information risk. In particular, the analysis of half-hour trading intervals

[4] Note, however, that this does not imply that herd behavior is necessarily short-lived. On the contrary, Park and Sabourian (2011) show that herds can be quite persistent.

[5] Chang et al. (2000) and Chiang and Zheng (2010) identify herd behavior by analyzing the clustering of individual stock returns around a market consensus. While this empirical approach does not require investor specific data, it seems to be less closely connected to microeconomic herding theory.

reveals a strong and significant co-movement of trading activity and the herding intensity of institutional traders. In contrast to Hypothesis 2, however, our results do not suggest an asymmetric impact of market stress on herding intensity. In fact, we find that both, sell as well as buy herding slightly increased in the German stock market during the 2007 European financial crisis.

The paper is structured as follows: Section 2 provides the theoretical framework of our analysis. Section 3 introduces the simulation setup and derives the hypotheses on the role of information risk and market stress for herding intensity. Section 4 introduces the empirical herding measure of Sias (2004). Section 5 presents the data and shows the empirical results. Section 6 concludes.

2 Information risk and market stress in a herd model

Section 2.1 briefly reviews the model of Park and Sabourian (2011), which is the theoretical basis of our further analysis of the role of information risk and market stress for herding intensity. Section 2.2 discusses how to define and measure herding intensity in the model and its simulation. Section 2.3 explains how information risk and the degree of market stress are reflected in the model.

2.1 The herd model

Park and Sabourian (2011) consider a sequential trading model à la Glosten and Milgrom (1985) consisting of a single asset, informed and noise traders, and a market maker. The model assumes rational expectations and common knowledge of its structure.

The Asset: There is a single risky asset with unknown fundamental value $V \in \{V_1, V_2, V_3\}$, where $V_1 < V_2 < V_3$. Its distribution is given by $0 < P(V = V_j) < 1$ for $j = 1, 2, 3$ where $\sum_{j=1}^{3} P(V = V_j) = 1$. The asset is traded over $t = 1, \ldots, T$

consecutive points in time. Thus, the trading period under consideration is $[0, T]$. In Section 3, we will choose $T = 100$ for simulating the model.

The Traders: Traders arrive one at a time in a random exogenous order in the market and decide to buy, sell or not to trade one unit of the asset at the quoted bid and ask prices.[6] Traders are either informed traders or noise traders. The fraction of informed traders is denoted by μ. Informed traders base their decision to buy, sell or not to trade on their expectations regarding the asset's true value. In addition to the publicly available information consisting of the history of trades H_t, i.e. all trades observed until period t, informed traders form their expectations according to a private signal $S \in \{S_1, S_2, S_3\}$ on the fundamental value of the asset. They will buy (sell) one unit of the asset if their expected value of the asset conditioned on their information set is strictly greater (smaller) than the ask (bid) price. Otherwise, informed traders choose not to trade. In the empirical herding literature, institutional investors are seen as a typical example for informed traders. Noise traders trade randomly, i.e. they decide to buy, sell or not to trade with equal probability of 1/3.

The Private Signal: The distribution of signals is conditioned on the true value of the asset, i.e. $P(S = S_i \mid V = V_j) = p^{ij}$ with $0 < p^{ij} < 1$ and $\sum_{i=1}^{3} p^{ij} = 1$ for all $i, j = 1, 2, 3$. For each i, the shape of a private signal S_i is given by p^{ij}, $j = 1, 2, 3$. In particular, Park and Sabourian (2011) define a signal S_i to be

- monotone decreasing iff $p^{i1} > p^{i2} > p^{i3}$,
- monotone increasing iff $p^{i1} < p^{i2} < p^{i3}$,
- u-shaped iff $p^{i1} > p^{i2}$ and $p^{i2} < p^{i3}$.

[6] Note that the present model can also be interpreted as one of endogenous trading by assuming that information arrives slowly in the market, i.e. at each instant only one trader receives information about the traded asset ,compare Chari and Kehoe (2004). The effect of endogenous timing of trades has also been studied experimentally by Park and Sgroi (2012).

Park and Sabourian (2011) show that a necessary condition for herding is that there exists a u-shaped signal. In accordance with Park and Sabourian (2011), we consider the case where one signal is u-shaped and both, optimists and pessimists are present in the market, i.e. one signal is monotone increasing (optimist) and another signal is monotone decreasing (pessimist). In our simulation exercise, we further assume that there are more optimists in "good times", i.e. $p^{13} < p^{23} < p^{33}$, and more pessimists in "bad times", i.e. $p^{11} > p^{21} > p^{31}$. In the following, those signal structures are called *feasible*.

The Market Maker: Trading takes place in interaction with a market maker who quotes a bid and ask price. The market maker accesses only publicly available information and is subject to perfect competition such that he makes zero-expected profit. Thus, he sets the ask (sell) price equal to his expected value of the asset given a buy (sell) order and the public information. Formally, he sets $ask_t = E[V|H_t \cup \{a_t = buy\}]$ and $bid_t = E[V|H_t \cup \{a_t = sell\}]$, where a_t is the action of a trader in time t.

2.2 Herding and herding intensity

Park and Sabourian (2011) describe herding as a "history-induced switch of opinion [of a certain informed trader] in the direction of the crowd". More precisely, in the model context, herding is a defined as follows:

Definition: *Herding*

Let b_t (s_t) be the number of buys (sells) observed until period t at history H_t. A trader with signal S buy herds in period t at history H_t if and only if

(i) $E[V|S] \leq ask_1$ *(Informed trader with signal S does not buy initially),*

(ii) $E[V|S, H_t] > ask_t$ *(Informed trader with signal S buys in t)*

(iii) $b_t > s_t$ *(The history of trades contains more buys than sells, i.e. the crowd buys)*

Analogously, a trader with signal S sell herds in period t at history H_t if and only if

(i) $E[V|S] \geq bid_1$ *(Informed trader with signal S does not sell initially),*

(ii) $E[V|S, H_t] < bid_t$ *(Informed trader with signal S sells in t)*

(iii) $b_t < s_t$ *(The history of trades contains more sells than buys, i.e. the crowd sells)*

Note that this definition is less restrictive than the one used in Park and Sabourian (2011). Above, herding refers to switches from not buying (not selling) to buying (selling), whereas Park and Sabourian (2011) define herding to be extreme switches from selling to buying and vice versa. However, as they already noted, allowing herd behavior to include switches from holding to selling or buying is a legitimate extension which they do not consider only to be consistent with some of the earlier theoretical work on herding. For our empirical application, including switches from holding to selling or buying is more appropriate because such switches also contribute to stock price movements.[7]

Notice further that item (iii) also differs slightly from the original definition of Park and Sabourian (2011). There, (iii) reads $E[V|H_t] > E[V]$ for buy herding (and analogously for sell herding) and is based on the idea that prices rise (fall) when there are more (less) buys than sells. However, for an empirical analysis it is more convenient to base the definition of herding more closely to the term "following the crowd": While we can observe the number of buys and sells, the market's expectation of the asset's true value, $E[V|H_t]$, can at best be approximated.

By definition, only informed traders can herd. Therefore, herding intensity is defined as the number of trades where traders engaged in herd behavior as a fraction of the total

[7]Note that it would also be possible to include switches from selling or buying to holding. However, we are mainly interested in herd behavior which potentially contributes to stock price volatility. Any switch to holding cannot amplify stock price movements or cause the stock price to move into the wrong direction. The only empirical effect would be a reduction in trading volume. By model assumption, however, liquidity is steadily provided by noise traders.

number of *informed* trades.[8] Specifically, for each trading period $[0, T]$, sell herding intensity (SHI) is measured as

$$\text{Sell herding intensity} = \frac{\#\text{herding sells}}{\#\text{informed trades}}$$

and the definition for buy herding intensity (BHI) follows analogously.

2.3 Information risk and market stress in the model

Easley et al. (1996) introduce information risk as the probability that an observed trade was executed by an informed trader. Thus, information risk coincides with the parameter μ, the fraction of informed traders, in the model of Park and Sabourian (2011). Therefore, we derive our theoretical prediction for the effect of information risk on herding intensity by conducting comparative static analysis for herding intensity with respect to changes in μ.

Times of market stress are typically understood as times of deteriorated economic outlook and increased risk, when markets become more pessimistic and more uncertain. In the model of Park and Sabourian (2011), these changes in the distribution of the fundamental value of the asset are reflected in lower $\mathbb{E}[V]$ and higher $\text{Var}(V)$. Both effects can be summarized using the coefficient of variation, $VC(V) := \sqrt{\text{Var}(V)}/\mathbb{E}[V]$, as a measure of market stress. The higher $VC(V)$, the higher the degree of market stress.

3 Simulating a herd model

Empirical studies on herd behavior typically derive results for herding intensity as an average for a large set of stocks. These stocks are likely to differ in their characteristics, which in terms of the herding model means that each stock is described by a distinct

[8] In order to remain close to our empirical application we consider only trades from informed types and exclude holds, since we investigate institutional trading and our data does not cover holds.

parameterization for the fraction of informed traders, the prior distribution of the asset, and the distribution of the private signals. Moreover, these characteristics cannot be expected to be constant over time. In accordance with the empirical literature, we are therefore particularly interested in the comparative statics of herding intensity as an average over a broad range of parameterizations. Yet, the model of Park and Sabourian (2011) is not designed to allow the derivation of a tractable closed form solution for the average herding intensity expected for a broad range of model parameterizations. In fact, even for a single parameterization, comparative static results cannot be obtained analytically, see Appendix. As a consequence, we derive comparative static results on the role of information risk and market stress on average herding intensity by means of numerical model simulations.

In empirical applications, it is difficult to decide whether a trader herds or not since researchers have no access to private signals. In contrast, in the simulation of the model we can determine for each trade whether herding actually occurred. As a result, for each simulation, the exact degree of herding intensity can be calculated. The choice of parameter values and the simulation setup is explained below.

3.1 Simulation setup

In our simulations, we assume that the fraction of informed traders, μ, is taken from $\mathcal{M} = \{0.05, 0.1, 0.15, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95\}$, i.e. $|\mathcal{M}| = 13$. Note that values $\{0.2, ..., 0.7\}$ correspond to the range of market shares of institutional investors observed for our sample period, compare Kremer and Nautz (2013a). The finer grid for values close to 0 and 1 was chosen to visualize potentially strange model behavior for very small and very large μ, respectively.[9]

[9] Park and Sabourian (2011) find that for certain parameterizations μ has to be smaller than an upper bound strictly smaller than 1 in order to allow for herding in the model.

The prior distribution for an asset, $P(V)$, is taken from the set

$$\mathcal{P} = \{P(V) : P(V_j) \in \{0.1, 0.2, \ldots, 0.8\} \text{ for } j = 1, 2, 3 \text{ and } \sum_{j=1}^{3} P(V_j) = 1\}.$$

Thereby, we consider only situations where the risky asset V takes each value V_1, V_2, V_3 with positive probability. This parametrization produces $|\mathcal{P}| = 36$ different asset distributions.

The conditional signal distribution, $P(S|V)$ is chosen from the set $\mathcal{C}$ which includes all feasible signal structures contained in

$$\tilde{\mathcal{C}} = \{P(S|V) : p^{ij} \in \{0.1, 0.2, \ldots, 0.8\} \text{ for } i, j = 1, 2, 3\}.$$

As a result, the simulation accounts for $|\mathcal{C}| = 41$ different signal structures.

Considering all possible combinations of the above parameters we obtain $\Omega := \mathcal{M} \times \mathcal{P} \times \mathcal{C}$, where $|\Omega| = 13 \times 36 \times 41 = 19188$. Each element $\omega = (\mu, P(V), P(S|V)) \in \Omega$ represents a specific stock. Each stock is traded over $T = 100$ points of time. For each model parameterization, the simulation is repeated 2000 times which produces more than 380 million simulated trades to analyze.

The results of these model simulations are used to derive predictions on the effect of changes in information risk on average herding intensity as follows: In a first step, we fix $\mu \in \mathcal{M}$ and calculate average herding intensity as the average across all parameterizations in $\{\mu\} \times \mathcal{P} \times \mathcal{C}$. In a second step, we evaluate how average herding intensity varies with μ. Accordingly, to analyze the effect of market stress on average herding intensity, we fix $P(V) \in \mathcal{P}$ and calculate average herding intensity across all parameterizations in $\mathcal{M} \times \{P(V)\} \times \mathcal{C}$. Next, we evaluate how average herding intensity varies with the distribution of the asset, $P(V)$, where the degree of market stress implied by $P(V)$ is proxied by its coefficient of variation, $VC(V)$.

3.2 Simulation Results

Figure 1 shows boxplots for average herding intensity for sell and buy herding, respectively, over 2000 simulations for parameterizations of the model that differ only in the fraction of informed traders. The simulation results clearly indicate that both, average buy and sell herding intensity increase in the fraction of informed traders in a symmetric way. Intuitively, private information may be easier dominated by the information contained in the history of trades as each preceding trade is more likely to be carried out by an informed type. The simulation results further suggest a weaker increase in herding intensity as well as an increase in the variance of herding intensity when μ approaches one. This could be explained by the increased bid-ask spread induced by an increase in the fraction of informed traders, making a switch from not buying (not selling) to buying (selling) less likely. Note that for our empirically relevant range of $\mu \in [0.2, 0.7]$ the increase in herding intensity is steep and each set of parameterizations exhibits only small variations across the 2000 simulations.

The fraction of informed traders determines the probability for the market maker to encounter an informed trader and, thus, the information risk in the market. Therefore, the simulation results shown in Figure 1 can be summarized as follows:

Hypothesis 1 (Information Risk and Herding Intensity)**.** *Average sell and buy herding intensity should increase in information risk.*

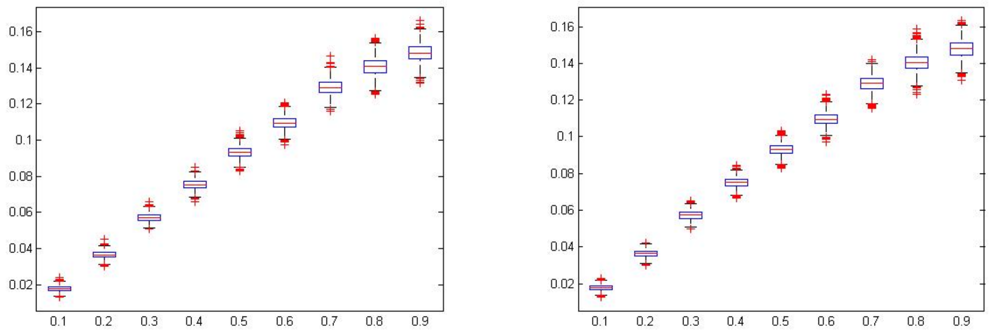
Figure 2 shows sell and buy herding intensity for parameterizations that differ only in the degree of market stress as it is reflected by the variation coefficient, $\sqrt{\mathrm{Var}(V)}/\mathbb{E}[V]$, of the fundamental value.[10] The higher the variation coefficient, the more severe the market stress. In contrast to information risk, the impact of market stress on herding is highly asymmetrical. For sell herding intensity, the simulation results demonstrate a strong positive relationship of average herding intensity and the variation coefficient.

[10] Unlike in Figure 1 we plot the average herding intensity across 2000 simulations instead of boxplots, for the sake of readability. The variation of herding intensity across 2000 simulation is, however, comparable to the variations in Figure 1.

Figure 1: Information Risk and Herding Intensity

(a) Sell Herding

(b) Buy Herding



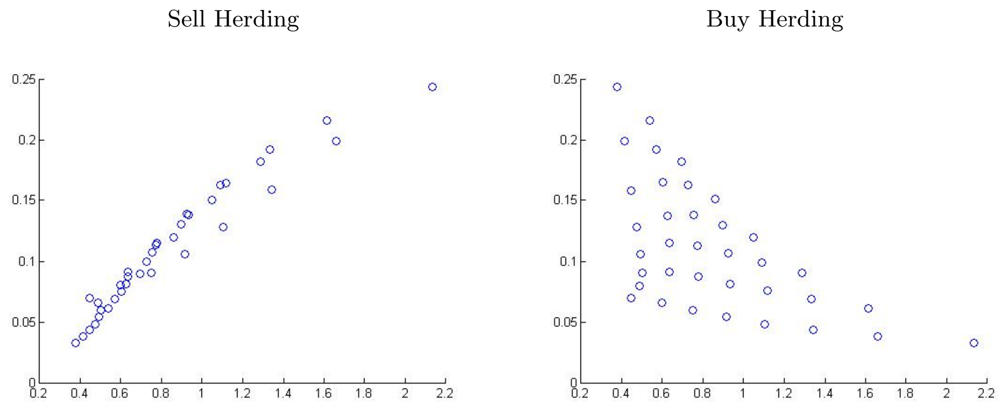
Notes: Sell and buy herding intensity, respectively, are plotted against the fraction of informed traders. The boxplots show the variation across 2000 simulations of herding intensity for parameterization $\{\mu\} \times \mathcal{P} \times \mathcal{C}$, where the fraction of informed traders, μ, is plotted along the horizontal. On the ordinate we plot herding intensity as a fraction of informed traders that engaged in herd behavior. The central mark of each box is the median, the edges of the boxes are the 25th and 75th percentiles, the whiskers are the most extreme data points.

Therefore, the higher the degree of market stress, the higher the average sell herding intensity to be expected in a heterogenous stock market. For buy herding intensity, however, the effect is clearly less pronounced. To explain this asymmetry, consider an increase of the variation coefficient that is mainly driven by a decrease of the expected value of the asset $\mathbb{E}[V]$. In this case, a greater variation coefficient should clearly increase sell herding while buy herding should be expected to occur less frequently.[11] We summarize our simulation results obtained for the relationship between our proxy for market stress and average herding intensity as follows:

Hypothesis 2 (Herding Intensity and Market Stress)**.** *Average buy herding intensity should decrease with market stress, whereas sell herding intensity should increase.*

[11]In fact, simulation results for buy herding were similar to those for obtained sell herding, if we plotted average buy herding intensity against $\sqrt{\mathrm{Var}(V)}\mathbb{E}[V]$.

Figure 2: Market Stress and Herding Intensity



Notes: Sell and buy herding intensity, respectively, are plotted against the variation coefficient. Each dot shows the herding intensity averaged across 2000 simulations for parameterization $\mathcal{M} \times \{P(V)\} \times \mathcal{C}$, where the variation coefficient, $VC(V)$, induced by the asset's distribution, $P(V)$, is plotted along the horizontal. On the ordinate we plot herding intensity as a fraction of informed traders that engaged in herd behavior across 2000 simulations.

4 The Empirical Herding Measure

The dynamic herding measure proposed by Sias (2004) is designed to explore whether investors follow each others' trades by examining the correlation between the traders' buying tendency over time. The Sias herding measure is, therefore, particularly appropriate for high-frequent data. Similar to the static herding measure proposed by Lakonishok et al. (1992), the starting point of the Sias measure is the number of buyers as a fraction of all traders. Specifically, consider a number of N_{it} institutions trading in stock i at time t. Out of these N_{it} institutions, a number of b_{it} buys stock i at time t. The buyer ratio br_{it} is then defined as $br_{it} = \frac{b_{it}}{N_{it}}$. According to Sias (2004), the ratio is standardized to have zero mean and unit variance:

$$\Delta_{it} = \frac{br_{it} - \bar{br}_t}{\sigma(br_{it})}, \tag{1}$$

where $\sigma(br_{it})$ is the cross sectional standard deviation of buyer ratios across I stocks at time t. The Sias herding measure is based on the correlation between the standardized buyer ratios in consecutive periods:

$$\Delta_{it} = \beta_t \Delta_{i,t-1} + \epsilon_{it}. \tag{2}$$

The cross-sectional regression is estimated for each time t and then the Sias measure for herding intensity is calculated as the time-series average of the estimated coefficients: $Sias = \frac{\sum_{t=2}^{T} \beta_t}{T-1}$. It is worth emphasizing that this kind of averaging is very much in line with the way we calculate average herding intensity in the model simulation.

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

$$\begin{aligned}\beta_t = \rho(\Delta_{it}, \Delta_{i,t-1}) = &\left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \frac{(D_{nit} - \bar{br}_t)(D_{ni,t-1} - \bar{br}_{t-1})}{N_{it} N_{i,t-1}}\right] \\ &+ \left[\frac{1}{(I-1)\sigma(br_{it})\sigma(br_{i,t-1})}\right] \sum_{i=1}^{I} \left[\sum_{n=1}^{N_{it}} \sum_{m=1, m\neq n}^{N_{i,t-1}} \frac{(D_{nit} - \bar{br}_t)(D_{mi,t-1} - \bar{br}_{t-1})}{N_{it} N_{i,t-1}}\right], \end{aligned} \tag{3}$$

where I is the number of stocks traded. D_{nit} is a dummy variable that equals one if institution n is a buyer in i at time t and zero otherwise. $D_{mi,t-1}$ is a dummy variable that equals one if trader m (who is different from trader n) is a buyer at time $t-1$. Therefore, the first part of the measure represents the component of the cross-sectional inter-temporal correlation that results from institutions following their own strategies when buying or selling the same stocks over adjacent time intervals. The second part indicates the portion of correlation resulting from institutions following the trades of others over adjacent time intervals. According to Sias (2004), a positive correlation that results from institutions following other institutions, i.e., the latter part of the decomposed correlation, can be regarded as evidence for herd behavior. In the following empirical analysis, we shall therefore focus on the latter term of equation (3) which we denote by $\overline{Sias}$.

According to Choi and Sias (2009), Equation (3) can be further decomposed to distinguish between the correlations associated with "buy herding" and "sell herding". Hence, stocks are classified by whether institutions bought in $t-1$ ($br_{i,t-1} > 0.5$) or sold in $t-1$ ($br_{i,t-1} < 0.5$).

5 Information risk, market turbulence and herding intensity: Empirical results

5.1 The Data Set

The empirical part of the paper is based on disaggregated data covering *all* real-time transactions carried out in the German stock market in shares included in the DAX 30, i.e., the index of the 30 largest and most liquid stocks. The study covers data from July 2006 until March 2009, i.e. a total of 698 trading days. Stocks were selected according to the index composition valid on March 31, 2009. Over the observation period 1,044 institutions traded in DAX 30 stocks on German stock exchanges.[12]

The empirical herding literature has often been impeded by data availability problems. In contrast to data collected from, say, quarterly balance sheets or anonymous transaction data, our data set is both, high-frequent and investor-specific. These data have already been used by two companion papers: While Kremer and Nautz (2013a) demonstrate the importance of both features of the data for resulting herding measures, Kremer and Nautz (2013b) confirm a destabilizing impact of herds on stock prices.

The current paper builds on these studies in two important aspects. First, to the best of our knowledge, this paper is the first that analyzes *intra-day* herding intensity

[12] 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. See Kremer and Nautz (2013a,b) for more detailed information about the data.

using investor-specific data. Second, similar to the bulk of the empirical literature, the empirical analyses of Kremer and Nautz (2013a,b) are only loosely connected to herding theory. In contrast, the current paper tests new theory-based hypotheses on the role of information risk and market stress for herding intensity.

5.2 Information risk and herding intensity

The more informed traders are active in a market, the higher are the probability of informed trading and, thus, information risk. According to Hypothesis 1, average herding intensity should increase with information risk reflected in the parameter μ, the fraction of informed traders. In the following, we use for two empirical proxies for the level of information risk: i) the number of active institutional traders and ii) the share of the institutional trading volume.

According to e.g. Foster and Viswanathan (1993) and Tannous et al. (2013), the fraction of informed traders and, thus, information risk cannot be expected to be constant over a trading day. In order to account for intra-day trading patterns in the German stock market, we divide each trading day into 17 half-hour intervals. A trading day is defined as the opening hours of the trading platform Xetra (9 a.m. to 5:30 p.m.), on which the bulk of trades occur. The use of half-hour intervals ensures that the number of active institutions is sufficiently high for calculating intra-day herding measures.[13] The first two columns of Table 1 show how both empirical proxies for information risk are distributed within a day. Apparently, institutional traders are more active at the opening and closing intervals, irrespective of the measure of trading activity.

In order to investigate the intra-day pattern of herding intensity, we calculate the Sias herding measure for each half-hour time interval separately. The results of this exercise are also shown in Table 1. The third column shows for each interval the overall Sias measure ($Sias$) which is based on the average correlation of buy ratios between

[13] For sake of robustness, we also divided the trading day into 9 one-hour intervals but our main results do not depend on this choice. For brevity, results are not shown but are available on request.

two intervals, see Equation (2) in Section 4. Following Sias (2004), this correlation may overstate the true herding intensity because it does not account for correlation which results from traders who follow themselves. It is a distinguishing feature of our investor-specific data that it allows to address that problem even on an intra-day basis. In particular, column four reports the correlation due to investors following the trades of others ($\overline{Sias}$), see Equation (3).

Table 1 offers several insights concerning the intra-day pattern of institutional herding. First of all, both Sias measures provide strong evidence for the presence of herding for each half-hour interval of the trading day. Second, intra-day herding measures are significantly larger than those obtained for data with lower-frequency, compare Kremer and Nautz (2013a,b). Third, the sizable differences between $Sias$ and $\overline{Sias}$ highlights the importance of using investor-specific data. Finally, note that herding intensity is relatively high (9.92%) at market opening, while the peak of herding intensity (12.86%) is found to be at 4 p.m. – 4:30 p.m. CET, one half-hour interval after the US market has opened.

How is the observed intra-day variation of information risk related to the intra-day herding intensity of institutional investors? The Sias herding measure depends on the trading behavior of two subsequent time periods. Therefore, for each time interval herding intensity is compared with the average information risk of the corresponding time intervals.[14] Figure 3 reveals a strong intra-day co-movement between both proxies of information risk and $\overline{Sias}$. In fact, we find overwhelming evidence in favor of Hypothesis 1: the null-hypothesis of zero correlation between information risk and herding intensity can be rejected irrespective of the underlying proxy of information risk. For example, the rank-correlation coefficient between the average trading volume and the

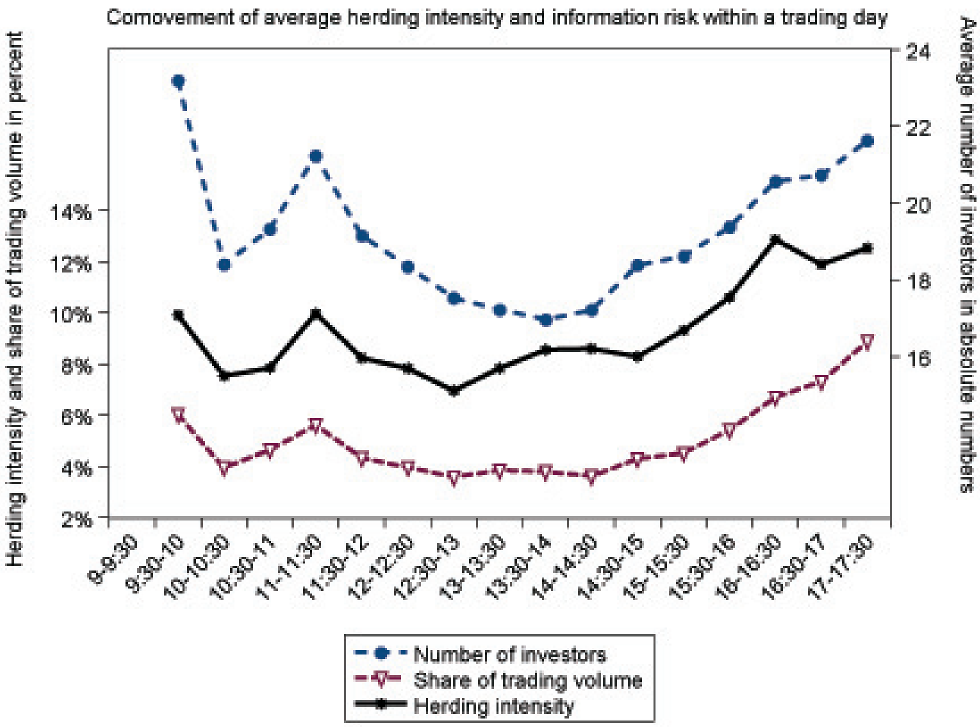
[14]Note that this is line with the intuition from the herd model of Park and Sabourian (2011). On the one hand, high information risk in $t-1$ leads institutional investors to believe that there is a high degree of information contained in previously observed trades. On the other hand, high information risk in t ensures that there is a high number of potential herders active in the market. Both effects contribute positively to herding intensity in period t.

Table 1: Information Risk and Herding Intensity within a Trading Day

	Information risk		Herding intensity	
Time	*Traders*	*Trading Volume*	*Sias*	$\overline{Sias}$
09:00 - 09:30	25.33	6.73	–	–
09:30 - 10:00	21.05	5.34	25.92 (0.23)	9.92 (0.26)
10:00 - 10:30	15.75	2.57	28.59 (0.22)	7.54 (0.24)
10:30 - 11:00	22.88	6.73	30.43 (0.29)	7.85 (0.23)
11:00 - 11:30	19.58	4.51	34.30 (0.31)	9.98 (0.22)
11:30 - 12:00	18.72	4.15	33.98 (0.29)	8.24 (0.23)
12:00 - 12:30	17.96	3.77	33.91 (0.30)	7.83 (0.24)
12:30 - 01:00	17.08	3.39	33.81 (0.25)	6.96 (0.21)
01:00 - 01:30	17.36	4.31	33.28 (0.24)	7.84 (0.21)
01:30 - 02:00	16.57	3.28	34.00 (0.28)	8.56 (0.21)
02:00 - 02:30	17.85	3.96	34.74 (0.25)	8.60 (0.26)
02:30 - 03:00	18.90	4.63	33.38 (0.24)	8.29 (0.26)
03:00 - 03:30	18.32	4.42	34.21 (0.26)	9.31 (0.26)
03:30 - 04:00	20.42	6.43	34.19 (0.28)	10.60 (0.26)
04:00 - 04:30	20.70	6.98	35.65 (0.28)	12.86 (0.26)
04:30 - 05:00	20.74	7.64	34.62 (0.27)	11.90 (0.26)
05:00 - 05:30	22.50	10.13	32.94 (0.28)	12.53 (0.26)

Notes: The table shows how information risk and herding intensity evolves over the trading day. On the predominant German platform Xetra®, trading takes place from 9 a.m. till 5.30 p.m. CET. *Traders* denotes the average number of active institutional traders, *Trading Volume* refers to the average percentage share of the daily trading volume of institutional investors. For instance, on average, 6.73% of the daily institutional trading volume appeared from 9 a.m. to 9:30 a.m. in the sample period. *Sias* and $\overline{Sias}$ represent the overall and the decomposed Sias herding measure, where the latter only considers institutions that follow the trades of others, see Equation (3). Standard errors are given in parentheses.

Figure 3: Information Risk and Average Herding Intensity within a Trading Day



corresponding Sias measure is 0.80, which is significantly above zero at the 1% level.[15] This result is in line with the experimental findings of Park and Sgroi (2012). They find that traders with relatively strong signals trade first, while potential herders delay. This behavior might also explain our finding that herding in the DAX increases following the opening of the U.S. stock market.

[15] More precisely, the associated p-value of the rank-test is 0.0003. Note that a rank correlation coefficient might be more appropriate than the standard correlation coefficient, since it accounts for the potentially non-linear relation between information risk and herding intensity suggested by the numerical simulation of the herd model, see Figure 1. Results of alternative tests are not shown for brevity but are available on request.

5.3 Herding in times of market stress

According to Hypothesis 2, sell herding should increase in times of market stress when uncertainty increases and markets become more pessimistic about the value of the asset. In contrast, buy herding intensity should decline in a crisis. In our application, a natural candidate to test this hypothesis is the outbreak of the financial crisis. In order to investigate the effect of the crisis on herding intensity, we calculate sell and buy herding measures for the crisis and the pre-crisis period separately. The pre-crisis period ends on August 9, 2007 as this is widely considered as the starting date of the financial crisis in Europe, see e.g. European Central Bank (2007) and Abbassi and Linzert (2012).

Herding measures obtained before and during the crisis are displayed in Table 2. The results are hardly compatible with the predictions of the simulated model. At first sight, the statistically significant yet small increase in sell herding ($5.74 > 5.41$) is in line with theoretical expectations. However, buy herding intensity has definitely not decreased in the crisis period. In fact, buy herding has even increased ($5.09 > 4.10$).

How can this contradicting evidence be explained? Probably, the effects claimed by Hypothesis 2 hold but are overshadowed by counteracting factors. For example, Kremer and Nautz (2013b) show that the market share of institutional investors has dropped sharply since the outbreak of the financial crisis. If this drop in trading activity of financial institutions can be interpreted as a decline in information risk, then a crises-driven increase in sell herding could be ameliorated by an increase of sell herding due to lower information risk. However, in this case, a potential drop in information risk makes the observed increase in buy herding even more puzzling.

6 Conclusion

This paper analyzes how information risk and market stress affect herding intensity. To obtain theory-founded results, we conduct numerical simulations of the financial

Table 2: Herding Intensity - Before and During the Financial Crisis

Buy Herding	$Sias$	$\overline{Sias}$
Pre-crisis period	14.37 (0.37)	4.10 (0.10)
Crisis period	13.87 (0.35)	5.09 (0.11)
Sell Herding		
Pre-crisis period	18.87 (0.23)	5.41 (0.09)
Crisis period	15.65 (0.25)	5.74 (0.08)

Notes: This table reports adjusted ($\overline{Sias}$) and unadjusted ($Sias$) herding measures based on half-hour intervals estimated separately for the pre-crisis and the crisis period. The Sias measures are further decomposed into its buy and sell herding components, compare Section 4. Standard errors are given in parentheses.

market herding model of Park and Sabourian (2011). First, simulation results imply that average herding intensity should increase as information risk increases. Second, increased market stress should cause average sell herding intensity to surge while it should trigger a drop in buy herding intensity.

These theory-based hypotheses are tested using investor-specific and high-frequent trading data from the German stock market DAX. The empirical herding measure of Sias (2004) applied to intra-day data confirms the positive relationship between information risk and herding intensity. The empirical results regarding the impact of market stress on herding intensity, however, partly contradict the model simulation results. While the estimated increase in sell herding during the recent financial crisis is in line with the simulation result, the estimated increase in buy herding contradicts the simulation-based model prediction.

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A Appendix

A.1 Analytical results on herding intensity

We will now present an analytical formula for theoretical sell herding intensity in the context of the model of Park and Sabourian (2011). Investigating this formula more closely, we will see that the relationship between herding intensity and probability of informed trading ($= \mu$) as well as market turbulence ($= \sqrt{Var[V]}/E[V]$) is too complex to develop comparative statics analytically.

In fact, we can show that under certain conditions the expected number of herding sells $E[s^h_{T,\mathcal{M}}]$ is given by

$$E[s^h_{T,\mathcal{M}}] = \sum_{i=1}^{3} P(V_i) \left\{ \sum_{j=1}^{T} j \left(\frac{\mu P(S_2|V_i)}{\mu(P(S_2|V_i) + P(S_3|V_i) - \frac{1}{3}) + \frac{1}{3}} \right)^j \left[\sum_{k=j}^{T} P(\bar{S}_{T,\mathcal{M}} = k|V_i) \left(\frac{\mu(P(S_3|V_i) - \frac{1}{3}) + \frac{1}{3}}{\mu(P(S_2|V_i) + P(S_3|V_i) - \frac{1}{3}) + \frac{1}{3}} \right)^{k-j} \right] \right\}, \tag{4}$$

where $\mathcal{M} := \{\mu, P(V), P(S|V)\}$ be the parametrization of the model, $s^h_{T,\mathcal{M}}$ denotes the actual number of sell herds and $\bar{S}_{T,\mathcal{M}}$ is the number of sells that occur while S_2 engages in sell herding. The formula is mainly derived via application of Bayes' rule and the law of iterated application. To develop some intuition behind it, consider first only the term $\sum_{i=1}^{3} P(V_i) \{\cdot\}$. The factor $\{\cdot\}$ contains the estimated number of sell herds given a realization of the risky asset $V = V_i$. The probability weighted sum, thus is the expected number of sell herds over all possible states of the risky asset V. Now, consider the terms within the curly brackets, i.e. $\sum_{j=1}^{T} j \left(\frac{\mu P(S_2|V_i)}{\mu(P(S_3|V_i) - \frac{1}{3}) + \frac{1}{3}} \right)^j [\cdot]$. The number j stands for the number of herding sells in some history H_t. The factor $(\cdot)^j$ stands for the probability that the u-shaped informed trader S_2 arrives on the market j times and each time decides to sell, given that history H_t contains $k \geq j$ sells under which a herding sell can occur. The sum in brackets finally, describes the probability that $k - j$ sells stem from either noise traders or S_3 for all $k \geq j$ and given that k sells occur under which S_2 would engage in sell herding.

The proof for this formula and the theory behind it are currently provided on request and will be implemented in this appendix in later versions of this paper. The important thing to take away from this formula is that it is not feasible to conduct comparative statics of herding intensity analytically. First note, that there is a lot of complexity hidden in $P(\bar{S}_{T,\mathcal{M}}|V_i)$. This probability is impossible to compute analytically since we would need to calculate the probabilities of all history paths H_T. Depending on the model parameterization, we would need to calculate the probabilities of at least 6^T history paths, where 6 amounts to the number of different possible states of the model, we need to consider in each step. Moreover, the above formula only yields results for the expected number of herding sells for a given model parameterization. If wanted to generalize our assessment to arbitrary model parameterizations or the average number of herding sells for different model parameterizations, the tractability of expected herding sells would be reduced even further. Finally note, that 4 only provides the value for the number of herding sells. SHI, however, was defined as the number of herding sells divided by the number of informed trades. Consequently, the expected sell herding intensity would be given by the expectation of that quotient. Since the number of informed trades is also random variable that is not independent of the number of herding sells, $E[\frac{\text{\# herding sells}}{\text{\# informed trades}}]$ is even harder to compute.

But even if we were to agree that 4 is a good proxy to base our analytical discussion upon, comparative statics of the expected number of herding sells with respect to changes in μ and $P(V)$ would not be fruitful. For the latter simply note, that the complexity of the sum makes it impossible to isolate $E[V]$ or $Var[V]$ on the right hand side of equation (4). Regarding the probability of informed trading, it seems at first glance possible to differentiate the right hand side of equation (4) with respect to μ. The sign of the derivative, however, will depend on the signal structures for informed traders S_2 and S_3 as well as the distribution $P(V)$ of the risky asset which will prevent us from establishing general analytical results.