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The impact of information risk and market stress on institutional trading: New evidence through the lens of a simulated herd model

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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 show that buy and sell herding intensity should increase with information risk. Market stress should affect herding asymmetrically: while there is more sell herding when the market becomes more pessimistic and more uncertain, buy herding intensity should decrease. We test these predictions using intra-day herding measures based on 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. However, in contrast to the simulation results empirical herding measures indicate that buy herding has even slightly increased, not decreased, during the recent crisis period.

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 stability and efficiency 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 (see Brunnermeier (2001)). Given these potentially severe adverse effects of herd behavior on financial markets, this paper aims to shed more light on the determinants of herding intensity from a theoretical as well as an empirical perspective.

While it is generally understood that herd behavior has the potential to *create* times of market stress and uncertainty, this paper investigates whether this effect might be self-enforcing, i.e. whether *vice versa* increased market uncertainty provides breeding ground for herd behavior, thereby creating a vicious circle of high volatility regimes. In addition to uncertainty about the value of the asset, private information and information risk are further key-ingredients of herding theory. In herd models, information risk increases with the probability of trading with a counterpart holding private information about the value of the asset. Therefore, information risk increases with the fraction of informed traders, see Easley et al. (1996). The second contribution of this paper is to examine how information risk and, thus, the fraction of informed traders affect 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).[1] Their concepts were put into a financial market context most famously 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), the model of Park and Sabourian (2011) implies that herd behavior could be a relevant phenomenon even in modern financial markets. Therefore, the Park and Sabourian (2011) model serves as the theoretical framework for our analysis. Within

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

this model, we are able to investigate how changes in the degree of market stress and information risk affect expected herding intensity. However, herding models including the one of Park and Sabourian (2011) are designed to explain the causes for herd behavior and to examine its consequences rather than to provide comparative static results on herding intensity. To circumvent this problem, we perform numerical simulations for more than 19000 different parameterizations of the model generating about 380 million trades to analyze. This simulation exercise implies theory-guided predictions on the role of market stress and information risk on herding intensity. First, we find that an increase in information risk should result in an increase of both, buy and sell herding intensity. Second, an increase in market stress - measured by the variation coefficient of the risky asset - should cause a drop in buy herding intensity and an increase in sell herding intensity.

In the second part of the paper, we will test these predictions empirically. The empirical evidence on herding is often impeded by data availability problems. Former studies have either to rely on investor-specific but low-frequent data, or use high-frequent but anonymous transaction data, compare Wermers (1999) and Barber et al. (2009). In an empirical analysis of herd behavior, the data should be high-frequent since private information in financial markets is fast moving. As a consequence, the informational advantage from private signals can only be exploited for short time horizons.[2] 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. Moreover, the data ought to be investor-specific as we need to directly identify transactions by each trader in order to determine whether the investor is actually herding or not.

We contribute to the literature by analyzing an intra-day, investor-specific data set that is provided by the German Federal Financial Supervisory Authority (BaFin) and includes all real-time transactions in the major German stock index DAX 30 carried

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

out by banks and financial services institutions. Following the herding literature, we focus on the herding behavior of institutional investors for two reasons. First, it is plausible to assume that institutional investors are informed traders, who - from a model perspective - are the only traders prone to herd behavior. Second, 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 use the empirical herding measure proposed by Sias (2004) because it differentiates between traders that indeed follow predecessors and traders that simply follow themselves, for example, because they split their trades. To the best of our knowledge, the Sias measure has not been applied to intra-day data before.[3]

In line with our first simulation-based hypothesis, the empirical herding measure increases with information risk on an intra-day level. Note that this effect is also found by Zhou and Lai (2009) for the Hongkonk stock exchange using quarterly measures of information risk. In contrast, the evidence obtained for the role of market stress on herding is mixed. First, in line with the findings of Kremer and Nautz (2013a,b) obtained for lower-frequent data, the increase in sell herding intensity during the recent financial crisis period is only weak. Similar findings are provided by Hwang and Salmon (2004) for herding intensity during the Asian and the Russian crisis in the nineties. Second, however, contradicting the simulation results, buy herding has also increased not decreased in the crisis.

The rest of the paper is structured as follows: Section 2 briefly reviews the the herding model of Park and Sabourian (2011). 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. Section 5 presents 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) show that institutions exhibit herd behavior on a daily basis causing short-term instability of stock prices.

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. In Sections 4 and 5, empirical herding measures assume that the trading period $[0, T]$ corresponds to an half-hour interval.

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. Traders are either noise traders or informed traders. The fraction of noise traders is $1 - \mu$. They decide to buy, sell or not to trade with equal probability

of 1/3. In contrast, 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.

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 $0 < p^{ij} < 1$ for all $i, j = 1, 2, 3$ and $\sum_{i=1}^{3} p^{ij} = 1$ for all $j = 1, 2, 3$. The shape of a private signal S_i is given by p^{ij}, $j = 1, 2, 3$ for i fixed. 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 $p^{i2} < p^{i3}$.

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 only consider the interesting 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 *feasable*.

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 infor-

mation 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, thereby excluding switches from holding. 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.[4]

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.[5]

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 number of *informed* trades.[6] 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.

[4]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.

[5]Another technical problem with the model is that one can find certain parameterizations and construct certain histories such that $B_t > S_t$ does not imply $E[V|H_t] > E[V]$.

[6]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.

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 $\text{Var}(V)$. In a crisis period, 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 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.[7]

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

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

[7] 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.

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.

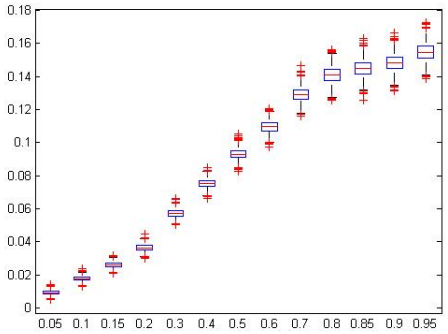
The results of these model simulations are used to derive predictions on the effect of changes in information risk on average herding intensity as follows: In a first step, we fix $\mu \in \mathcal{M}$ and calculate average herding intensity as the average across all parameterizations in $\{\mu\} \times \mathcal{P} \times \mathcal{C}$. 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

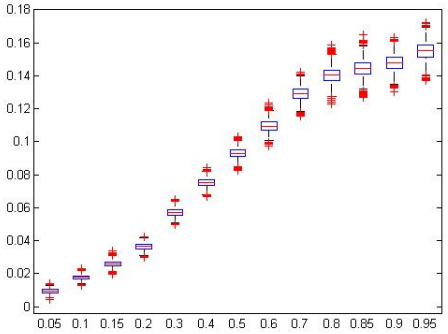
Figure 1 shows boxplots for average herding intensity for sell and buy herding, respectively, over 2000 simulations for parameterizations of the model that differ only in the fraction of informed traders. The simulation results clearly indicate that both, average buy and sell herding intensity increase in the fraction of informed traders in a symmetric way. Intuitively, the increase of herding intensity can be explained by the increased probability that a potential herder trades on the market due to the increase in μ. Moreover, private information may be easier dominated by the information contained in the history of trades as each preceeding trade is more likely to be carried out by an informed type. Note that the simulation results suggest a weaker increase in herding intensity as well as an increase in the variance of herding intensity when μ approaches the upper boundary. of μ can be explained by the increased bid-ask spread induced by

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 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.

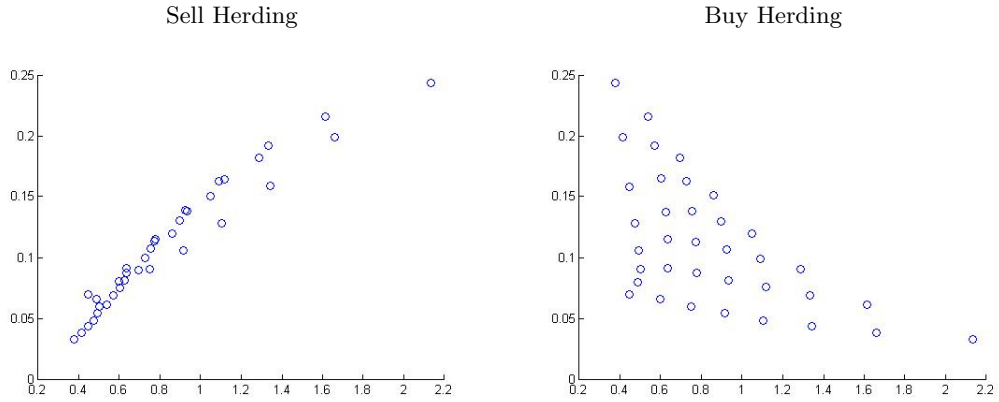
an increase in the fraction of informed traders, making a switch from not buying (not selling) to buying (selling) less likely. Note that for our empirically relevant range of $\mu \in [0.2, 0.7]$ the increase in herding intensity is steep and each set of parameterizations exhibits only small variations across the 2000 sumulations.

The fraction of informed traders determines the market maker's risk to trade with an informed trader and, thus, the probability of informed trading. 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 the probability of informed trading.*

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, $\sqrt{\text{Var}(V)}/\mathbb{E}[V]$,

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.

of the fundamental value.[8] 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. 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.[9]

[8] 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.

[9] In fact, simulation results for buy herding were similar to those for obtained sell herding, if we

We summarize this simulation result found 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.*

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 buyers 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} transactions, a number of b_{it} are buy transactions. The buyer ratio br_{it} is then defined as $br_{it} = \frac{b_{it}}{N_{it}}$. 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 (unadjusted) Sias measure for herding intensity $Sias$ is calculated as the time-series average of the estimated coefficients: $Sias = \frac{\sum_{t=2}^{T} \beta_t}{T-1}$. It worth emphasizing that this kind of averaging is very much in line with the way we calculated average herding intensity in the model simulation.

plotted average buy herding intensity against $\sqrt{\mathrm{Var}(V)}\mathbb{E}[V]$.

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:

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

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 resulting *adjusted* Sias measure denoted 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.[10]

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 for empirical herding measures, Kremer and Nautz (2013b) estimate the impact of various stock characteristics including size and past returns on herding intensity. They also confirm a destabilizing impact of herds on stock prices in the short-term.

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 using investor-specific data. Second, while the empirical studies of Kremer and Nautz (2013a,b) are only loosely connected to recent herding theory, the current paper tests new hypotheses on the role of information risk and market turbulence for herding intensity which have been derived from a simulated herd model.

[10]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.

5.2 Information risk and herding intensity

The more informed traders are active in a market, the higher are the probability of informed trading (PIN), the relevance of asymmetric information and, thus, information risk. This intuition has been confirmed in our numerical simulation of the Park and Sabourian herd model, see Section 2. According to Hypothesis 1, average herding intensity should increase with the fraction of informed traders (μ). In the following, we will exploit the information contained in our intra-day data to test this hypothesis empirically.

The fraction of informed traders and, thus, information risk is typically not constant over a trading day. Typically, institutional traders are particularly active at market opening and at times when new public information enters the market, compare e.g. Anderson and Bollerslev (1998). In order to investigate whether this also holds in the German stock market, we divide each trading day, defined as the opening period (9.00 a.m. to 5.30 p.m.) of the trading platform Xetra, where the bulk of trades occur, into 17 half-hour intervals. The use of half-hour intervals ensures that the number of active institutions is sufficiently high for calculating intra-day herding measures.[11] The first two columns of Table 1 shows how information risk, proxied by the average number of institutional traders and their trading volume, is distributed within a day. Therefore, institutional traders are indeed 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 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

[11] 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.

results from traders who follow themselves. It is a distinguishing feature of our investor-specific data that it allows to circumvent that problem even on an intra-day basis. In particular, column four reports the adjusted Sias measure ($\overline{Sias}$) that only accounts for true herding where traders follow the trades of others, 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 the unadjusted and the adjusted Sias measure 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 4.00 – 4:30 p.m. CET, when the US market has opened and a lot of new information flows into the German market. Interestingly, for both herding-intense intervals, trading activity is also relatively high.

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. Figure 3 reveals a strong intra-day co-movement between both proxies of information risk and the adjusted Sias measure. 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 share and the corresponding adjusted Sias measure is 0.80, which is significantly above zero at the 1% level.[12]

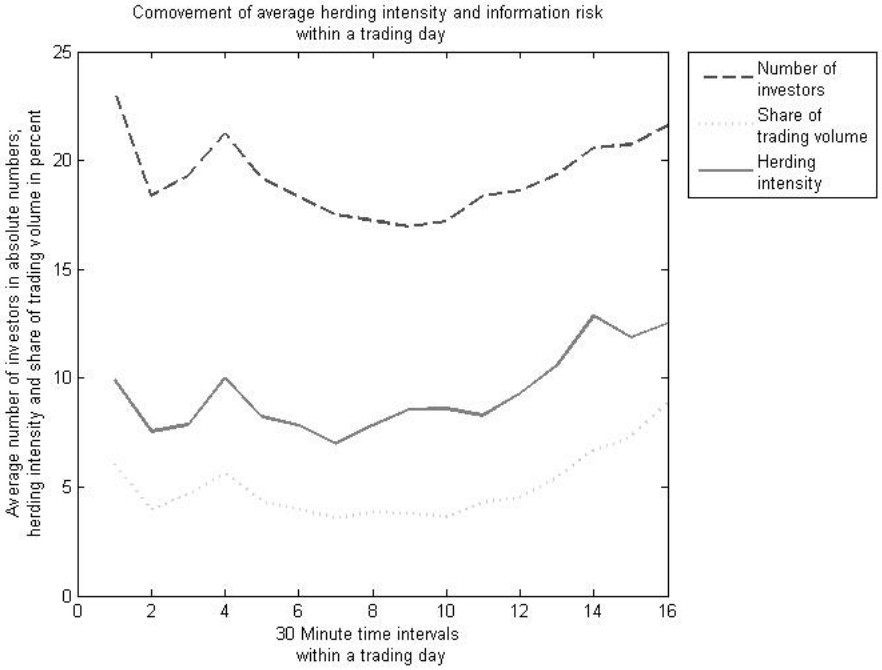
[12]More precisely, the associated p-value of the rank-test is 0.0003. Note that a rank correlation coefficient might be more appropriate than the standard correlation coefficient, since it accounts for the potentially non-linear relation between information risk and herding intensity suggested by the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

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

	Information risk		Herding intensity	
Time	$Traders$	$Volume$	$Sias$	$\overline{Sias}$
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, $Volume$ indicates in percentage points how total trading volume of institutional investors is distributed within a day. $Sias$ and $\overline{Sias}$ represent the overall and the adjusted Sias herding measure, where the latter only considers institutions that actually 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



5.3 Herding in times of market stress

In this section, we provide empirical evidence on our second result derived from the simulated herd model. 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 Kremer and Nautz (2013a,b).

brevity but are available on request.

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

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

Herding measures obtained before and during the crisis are displayed in Table 2.[13] 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 ($5.09 > 4.10$).[14]

How can this contradicting evidence be explained? Probably, the effects claimed by

[13]Note first that adjusted Sias measures $\overline{Sias}$ are significantly smaller than their unadjusted counterparts ($Sias$). Accordingly, without access to investor-specific data, the Sias measure would exaggerate the degree of true herding in a significant way.

[14]Similar negligible effects of the crisis on herding intensity have been found by Kremer and Nautz (2013a,b) for low-frequent data and the herding measure introduced by Lakonishok et al. (1992). Hwang and Salmon (2004) find that the Asian and in particular the Russian Crisis of the late nineties reduced herd behavior.

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.[15] 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

Particularly in times of economic uncertainty, herd behavior is often viewed as a significant threat for the stability and efficiency of financial markets. This paper analyzes how information risk and market turbulence affect herding intensity. To obtain theory-founded results, we conduct numerical simulations of the financial market herding model of Park and Sabourian (2011). First, we find 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 real-time 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 model prediction.

[15] A similar observation is made for information risk in the Euro-Area bond markets, see Barber et al. (2009).

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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 (= μ) 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 $P(\bar{S}_{T,\mathbb{M}}|V_i)$. 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.