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Information Risk, Market Stress and Institutional Herding in Financial Markets: New Evidence Through the Lens of a Simulated Model

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Abstract

This paper employs numerical simulations of the Park and Sabourian (2011) herd model to derive new theory-based predictions for how information risk and market stress influence aggregate herding intensity. We test these predictions empirically using a comprehensive data set of high-frequency and investor-specific trading data from the German stock market. Exploiting intra-day patterns of institutional trading behavior, we confirm that higher information risk increases both buy and sell herding. The model also explains why buy, not sell, herding is more pronounced during the financial crisis.

Keywords: Herd Behavior, Information Risk, Financial Crisis, Institutional Trading, Market Microstructure Model

JEL classification: D81, D82, G14

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1 Introduction

Herd behavior by investors can be a significant threat to the functioning of financial markets. The distorting effects of herding range from informational inefficiency to increased stock price volatility, or even bubbles and crashes. This paper derives two theory-based predictions for how information risk and market stress influence herding intensity that are tested with high-frequency and investor-specific trading data from the German stock market. We focus on information risk, defined as the probability of trading with a counterparty who holds private information about an asset (Easley et al. (1996)), since the presence of information asymmetries is a necessary condition for herd behavior. To date, however, it is not clear how herding intensity reacts to changes in information risk. A better understanding of this relationship could enhance a financial regulator's ability to identify herds. In light of the recent financial crisis, our second focus is on how herd behavior is affected by market stress, that is, situations in which investors are both pessimistic and uncertain about the stock's value. While herding certainly has the potential to *create* such market stress, it is not obvious whether the reverse relationship holds, but if it does, its existence threatens to create vicious cycles of economic downturns and high volatility regimes.

Building on Glosten and Milgrom (1985) and Easley and O'Hara (1987), the literature on information risk deals with estimating the information content of trades, see e.g. Hasbrouck (1991), Easley et al. (1996) and Easley et al. (1997). The effects of information risk on herding intensity, however, are underresearched.[1] While the proba-

[1] An exception is Zhou and Lai (2009) who provide evidence that herding is positively related to information risk measured by probability of informed trading (PIN), see e.g. Easley et al. (1997). The idea underlying the PIN measure is that there will be a distinct trading pattern on days when information events occur. More specifically, informed trading is possible only on days with information events. Since, moreover, information is not noisy, i.e. the information can never be wrong, days with information events (i.e. high information risk) are characterized by a strong accumulation of (informed) traders on one side of the market. The Lakonishok et al. (1992) measure employed by Zhou and Lai (2009) identifies herding also as the accumulation of traders on one side of the market. As a consequence, we would expect a positive relationship between PIN and the Lakonishok et al. (1992) herding measure by construction. The same should be true of the herding measure introduced by Sias (2004). Therefore, our estimations of information risk are not based on the PIN measure.

bility of informed trading is a key parameter in financial market herd models, compare e.g. Avery and Zemsky (1998) and Park and Sabourian (2011), to date these models have not been exploited to discover the impact of information risk on herding intensity. This is surprising, since the effects of information risk on herding intensity are far from obvious. On the one hand, an increase in information risk increases the average information content of an observed trade. As a consequence, traders update their beliefs more quickly and those investors that are susceptible to herding are more easily swayed to follow the crowd. On the other hand, increased information risk amplifies the market maker's adverse selection problem, compare Easley et al. (2002). Given the higher probability of trading at an informational disadvantage, the market maker quotes larger bid-ask spreads which tends to prevent potential herders from trading. Understanding which of these counteracting effects dominates could facilitate the detection of herds.

The impact of market stress on herd behavior has not been analyzed by the theoretical herding literature, either. Typically, herd models focus on the reverse relationship. For example, Park and Sabourian (2011) demonstrate that price paths tend to be more volatile in the presence of herd behavior. Agent based models proposed by, for example, Lee (1998) and Eguíluz and Zimmermann (2000) show that herd behavior contributes to fat tails and excess volatility in asset returns. A notable exception is Avery and Zemsky (1998), who show that herding is possible provided multiple sources of uncertainty exist. Their model does not imply, however, that more uncertainty actually leads to more herding. The prevalent unidirectional focus of the theoretical literature is particularly puzzling in light of the mixed evidence regarding the impact of market stress on herding intensity. Chiang and Zheng (2010) and Christie and Huang (1995) find that herding increases during times of market stress, whereas Kremer and Nautz (2013a,b) find that herding in the German stock market slightly decreased during the recent financial crisis, which is similar to the results of Hwang and Salmon (2004) for herding intensity during the Asian and the Russian crisis in the 1990s.

We base our theoretical analysis on the financial market herd model of Park and

Sabourian (2011), which can be viewed as a generalization of the seminal work of Avery and Zemsky (1998).[2] One important extension is the broader set of different information structures that allows a differentiated discussion of how information externalities may contribute to herd behavior under various market conditions including scenarios of high and low market stress. Relating investor herding to the shape of the information structure instead of to multi-dimensional uncertainty, Park and Sabourian (2011) identify more explicitly those situations in which the potential for herding is high. Consequently, the Park and Sabourian (2011) framework is more appropriate for finding and explaining high degrees of herding. In fact, experimental evidence suggests that the Avery and Zemsky (1998) framework discovers little or no herd behavior, see Cipriani and Guarino (2009).[3] In contrast, experiments based on the Park and Sabourian (2011) model find that herding in financial markets can be substantial, see Park and Sgroi (2012). In Park and Sabourian (2011), herding is triggered by information externalities that an investment decision by one agent imposes on subsequent agents' expectations about the asset value, see Bikhchandani et al. (1992) and Banerjee (1992).[4] Therefore, this model is a natural candidate for investigating the impact of information risk on herding intensity.[5]

[2]Similar to the bulk of the theoretical literature, both models define herd behavior as a switch in an agent's opinion toward that of the crowd, see Brunnermeier (2001). As herders ignore their private information, herd behavior is informationally inefficient and thus has the potential to distort prices and destabilize markets.

[3]Avery and Zemsky (1998) includes three model setups. The first setup extends the traditional herd model of Bikhchandani et al. (1992) by a price mechanism that prevents herd behavior. The most prominent experimental tests of the Avery and Zemsky (1998) framework, Drehmann et al. (2005) and Cipriani and Guarino (2005), focus on this setup and confirm the theoretical prediction of no herding. Cipriani and Guarino (2009), on the other hand, focus on one of the setups in which herd behavior is predicted, but again find only little evidence of it.

[4]Alternative drivers for herd behavior include reputational concerns as well as investigative herding. Reputational herd models modify the agents' objective functions such that their decisions are affected by positive externalities from a good reputation, see e.g. Scharfstein and Stein (1990), Graham (1999) and Dasgupta et al. (2011). Investigative herd models examine conditions under which investors may choose to base their decisions on the same information resulting in correlated trading behavior, see e.g. Froot et al. (1992) and Hirshleifer et al. (1994). For a survey of the early herding literature see Devenow and Welch (1996). For an in-depth discussion of how the herding literature ties into the social learning literature see Vives (1996).

[5]Other financial market herd models such as Lee (1998), Chari and Kehoe (2004), and Cipriani and Guarino (2008), investigate how investor herding is related to transaction costs, endogenous timing of trading decisions, and informational spillovers between different assets, respectively.

The history dependence of trading decisions in financial market herd models drastically impedes derivation of analytical results on herding intensity. This may explain why financial market herd models have not yet been exploited to make empirically testable predictions on the impact of information risk and market stress. Moreover, standard empirical herding measures, including Lakonishok et al. (1992) and Sias (2004), examine herding intensity on an *aggregate* level.[6] Therefore, a theory-guided empirical analysis of herd behavior requires theoretical predictions on herding intensity aggregated over investor groups, time periods, and heterogeneous stocks, which further complicates the derivation of analytical results.

In this paper we circumvent these problems by simulating the Park and Sabourian (2011) model for more than 13,000 different parameterizations that broadly cover the theoretical parameter space, generating about 2.6 billion trades for analysis. We obtain two testable hypotheses on aggregate herding intensity. First, an increase in information risk should result in a symmetric increase of buy and sell herding intensity. Second, high market stress should be found to have an asymmetric effect on herding intensity: while buy herding is predicted to surge during crisis periods, the simulation results suggest that sell herding intensity increases only moderately.

Both our predictions are confirmed by particularly appropriate intra-day, investor-specific data provided by the German Federal Financial Supervisory Authority (BaFin). Empirical studies typically have to rely on *either* investor-specific but low-frequency data (e.g. Lakonishok et al. (1992), Sias (2004), Wermers (1999)), *or* on high-frequency but anonymous transaction data (compare, e.g., Barber et al. (2009)). Kremer and Nautz (2013a) regress daily herding measures on size, volatility, and other stock characteristics to analyze the causes of herding. The current paper expands on these studies

[6] In Lakonishok et al. (1992), herding of a group of investors is measured as the tendency to accumulate on one side of the market. Specifically, the authors test whether the share of net buyers in individual stocks significantly deviates from the average share of net buyers across all stocks of the considered stock index. Sias (2004) investigates whether the accumulation of investors on one side of the market persists over time by measuring the cross-sectional correlation of the share of net buyers over adjacent time periods.

in two important aspects. First, similar to the bulk of the empirical literature, the empirical analyses of Kremer and Nautz (2013a,b) are only loosely connected to the theoretical herding literature. In contrast, the simulation-based predictions derived in this paper allow us to interpret evidence on herding through the lens of a financial market herd model. Second, to the best of our knowledge, this paper is the first to analyze *intra-day* herding intensity using investor-specific data. In line with herding theory, the use of *intra-day* data is particularly appropriate for measuring herd behavior induced by information externalities. Measuring herding at lower frequencies may bias the results because new information might have reached the market in the meantime, creating a new environment for investor behavior. The use of *investor-specific* data is particularly important as we need to directly identify transactions by each trader in order to determine whether an investor follows the observed actions of other traders. To assess herding empirically, we employ the herding measure proposed by Sias (2004). The dynamic nature of the Sias measure makes it particularly appropriate for the analysis of high-frequency data. Interestingly, the Sias measure has not yet been applied to intra-day data.

The remainder of the paper is structured as follows. In Section 2 we review the model of Park and Sabourian (2011). We define information risk as well as market stress and provide an initial qualitative assessment of their effect on herding intensity. Section 3 introduces the simulation setup and derives testable hypotheses regarding the role of information risk and market stress for aggregate herding intensity. Section 4 introduces the empirical herding measure. Section 5 presents the data and the empirical results. Section 6 concludes.

2 Information Risk and Market Stress in a Herd Model

2.1 The Model

Park and Sabourian (2011) consider a sequential trading model à la Glosten and Milgrom (1985), consisting of a single asset, both 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 $V_1 < V_2 < V_3$. Without loss of generality, let $V_1 = 0$, $V_2 = 1$ and $V_3 = 2$. The prior distribution $0 < P(V = V_j) < 1$ for $j = 1, 2, 3$ determines the degree of *public uncertainty* $\mathrm{Var}(V)$ about the asset's true value before trading has started. The asset is traded over T consecutive points in time. In Section 3, we choose $T = 100$ for the model simulation.

The Traders: Traders arrive in the market one at a time in a random exogenous order and decide to buy, sell, or not to trade one unit of the asset at the quoted bid and ask prices. 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 publicly available information consisting of the history of trades H_t, $t = 1, \ldots, T$, and the risky asset's prior distribution $P(V)$, informed traders form their expectations based on a private signal $S \in \{S_1, S_2, S_3\}$ regarding the true value of the asset. They buy (sell) one unit of the asset if their expected value of the asset $E[V \mid S, H_t]$ is strictly greater (smaller) than the ask (bid) price quoted by the market maker. Otherwise, informed traders choose not to trade. In the empirical herding literature, institutional investors are viewed as a typical example for informed traders. In contrast to informed traders, noise traders trade randomly, that is, they decide to buy, sell, or not to trade with

equal probability of 1/3. p_t denotes the price at which the asset is traded in period t.

The Private Signal: The distribution of the private signals S_1, S_2, S_3 is conditional on the true value of the asset. Denote the conditional signal matrix by $P(S = S_i \mid V = V_j) = (p^{ij})_{i,j=1,2,3}$. For each column j, the matrix is leftstochastic, i.e. $\sum_{i=1}^{3} p^{ij} = 1$. For each row i, $\sum_{j=1}^{3} p^{ij}$ is the likelihood that an informed trader receives the signal S_i. An informed trader's behavior is critically dependent on the shape of her private signal. Specifically, Park and Sabourian (2011) define a signal S_i to be

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

Traders with monotone signals are confident about the asset's true value and rarely change their trading decision. That is, an optimistic trader with an increasing signal will only buy or hold, whereas a pessimistic trader with a decreasing signal will only sell or hold. In contrast, traders with U-shaped signals face a high degree of uncertainty and may decide to buy, sell or hold. U-shaped traders are more easily swayed to change their initial trading decision as they observe trade histories H_t with a strong accumulation of traders on one side of the market. In fact, Park and Sabourian (2011) show that a U-shaped signal is a necessary condition for herding. Park and Sabourian (2011) also introduce hill-shaped signals which are necessary for contrarian behavior. Since contrarian behavior is self-defeating, its destabilizing effects are limited and thus of only secondary importance for financial markets. Consequently, we exclude hill-shaped signals from our analysis. In the following, we assume that S_1 is monotone decreasing, S_2 is U-shaped and S_3 is monotone increasing. The conditional private signal distribution $P(S \mid V)$ determines the degree of information asymmetry between market maker and informed traders. The less noisy the signal, the higher the informational advantage of the informed traders.

The Market Maker: Trading takes place in interaction with a market maker who quotes a bid and an ask price. The market maker only has access to public information and is subject to perfect competition such that he makes zero-expected profit. Accordingly, he sets the ask (bid) 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 period $t \geq 2$ and $H_t := \{(a_1, p_1), ..., (a_{t-1}, p_{t-1})\}$.

2.2 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." Thus, only informed traders can herd. More precisely, a herding trade is defined as follows:

Definition 1: *Herding*
Let b_t (s_t) be the number of buys (sells) observed until period t. An informed trader with signal S ***buy herds*** *in t at history H_t if the following three conditions hold:*

(BH1) $E[V|S] < E[V]$, i.e. an informed trader with signal S does not buy initially and is more pessimistic regarding the asset's true value than is the market maker.

(BH2) $E[V|S, H_t] > ask_t$, an informed trader with signal S buys in t.

(BH3) $b_t > s_t$, i.e. the history of trades contains more buys than sells: the crowd buys.

Analogously, an informed trader with signal S ***sell herds*** *in period t at history H_t if and only if (SH1) $E[V|S] > E[V]$, (SH2) $E[V|S, H_t] < bid_t$, and (SH3) $b_t < s_t$ hold simultaneously.*

Note that (BH1) and (SH1) imply that either buy or sell herding is possible for a given model parameterization. Our definition of herding is less restrictive than the one

used in Park and Sabourian (2011), who, for example, define buy herding as an extreme switch from selling initially to buying. In our definition, buy herding also includes switches from *holding* to buying, provided that the trader leans toward selling initially, compare (BH1) and (BH2).[7] As a consequence, herd traders always act informationally inefficiently as their trading decisions contradict their private information. From an empirical perspective, including switches from holding to selling or buying is important as these actions may drive amplified stock price movements.

(BH3) and (SH3) also differ slightly from Park and Sabourian (2011) in which, for example, buy herding requires $E[V|H_t] > E[V]$. This condition is based on the idea that prices rise when there are more buys than sells. However, this only holds if the prior distribution of the risky asset $P(V)$ is symmetric around the middle state V_2, i.e. $P(V_1) = P(V_3)$.[8] In fact, for asymmetric $P(V)$, it is possible that even though a history H_t contains more buys than sells, the price of the asset goes down (i.e., $E[V|H_t] < E[V]$). From an empirical perspective, asymmetric prior distributions $P(V)$ should not be ruled out a priori. Therefore, we modify the herding definition to ensure that a herder always *follows the crowd*.

The above definition enables us to decide whether or not a particular trade by a *single* investor at a specific point in time is a herd trade. In contrast, empirical herding measures are based on a number of trades by different investors observed over a certain time interval, see, e.g., Lakonishok et al. (1992) and Sias (2004). Since we aim to derive theory-based predictions on herd behavior that can be tested empirically, we need to aggregate herding in the model over time as well as over investors. We aggregate over time by considering all relevant trades from $t = 1, \ldots, T$. We aggregate over investors by calculating herding intensity for the whole group of informed traders. Therefore, we define *herding intensity (HI)* as the share of herding trades in the total number of

[7] According to Park and Sabourian (2011), such an extension of the herding definition is theoretically legitimate. They focus on the stricter version to be consistent with earlier theoretical work on herding.

[8] Note that Park and Sabourian (2011) assume symmetry of the risky asset's prior distribution throughout their paper (see Park and Sabourian (2011), p.980).

informed trades.

Definition 2: *Herding Intensity*

Let b_T^{in} and s_T^{in} be the number of buys and sells of informed traders observed until period T, i.e. during the entire time interval under consideration. Let b_T^h and s_T^h denote the corresponding number of buy and sell herding trades. Then,

$$\begin{aligned} \textit{Buy herding intensity (BHI)} &=: \frac{b_T^h}{b_T^{in} + s_T^{in}} \\ \textit{Sell herding intensity (SHI)} &=: \frac{s_T^h}{b_T^{in} + s_T^{in}} \end{aligned}$$

Standard empirical herding measures including those of Lakonishok et al. (1992) and Sias (2004) are calculated using only buys and sells, see Section 4. To be consistent with empirical herding measures, we exclude holds when calculating the number of informed trades in the definition of theoretical herding intensity.

2.3 Information Risk and Market Stress in the Herd Model

2.3.1 Information Risk

In Easley et al. (1996), information risk is the probability that a trade is executed by an informed trader. Hence, information risk coincides with the parameter μ, the fraction of informed traders, in the Park and Sabourian (2011) model. From a theoretical perspective, the effect of changes in μ on herding intensity is ambiguous. On the one hand, herding may increase with information risk because a higher μ implies that there are more potential herders (U-shaped traders) in the market. Indeed, due to the self-enforcing nature of herd behavior a higher μ contributes to longer-lasting herds and, hence, stronger herding intensity. Moreover, a higher fraction of informed traders implies that the average information content of a single trade increases. As

a consequence, informed traders update their beliefs more quickly and those traders that are susceptible to herd behavior are more easily swayed to change from buying to selling and vice versa. On the other hand, a rise in μ may also reduce herding intensity. Since the average information content per trade increases in μ, herds tend to break up more quickly as traders stop herding after observing fewer trades on the opposite side of the market. Higher information risk further amplifies the market maker's adverse selection problem, compare Easley et al. (2002). Given the higher probability of trading at an informational disadvantage, the market maker quotes larger bid-ask spreads in order to avoid losses. The larger spread, in turn, requires potential herders to observe much stronger accumulation of traders on one side of the market before they alter their trading decision.

2.3.2 Market Stress

Times of high market stress and crisis periods are typically understood as situations where investors are confronted with a deteriorating economic outlook and increased uncertainty about stock values, compare e.g. Schwert (2011). A negative economic outlook in the Park and Sabourian (2011) model is captured by low expectations regarding the asset's true value $E[V]$. A low $E[V]$ not only describes a deteriorated outlook by the public but also a high degree of pessimism among informed traders. First, lower public expectations $E[V]$ result in lower private expectations $E[V|S]$ for all informed traders. Second, there tend to be more decreasing signals (pessimists) among informed traders as well as fewer increasing signals (optimists) for low $E[V]$ than for high $E[V]$. Uncertainty in the Park and Sabourian (2011) can be sorted into two types: public uncertainty and informed trader uncertainty. *Public uncertainty* is given by the variance of the risky asset $\mathrm{Var}(V)$. *Informed trader uncertainty* (IU) is measured by the probabilities that informed traders receive a U-shaped signal conditional on V_j, $j = 1, 2, 3$: IU $:= \sum_{j=1}^{3} p^{2j}$. The higher IU, the more traders there are in the market with U-shaped signals and, hence, the higher the uncertainty among

informed traders.[9] In light of the recent financial crisis, we are particularly interested in comparing herding intensity in times of high market stress with the herding intensity predicted for more optimistic periods.

The overall effect of market stress on herding intensity is not obvious and crucially depends on model parameterization. In particular, buy and sell herding intensity may react differently to changes in market stress. Consider, for example, an increase in market stress due to a decrease in $E[V]$. More specifically, assume a shift of probability mass from V_3 to lower values. First, if, for a given model parameterization, buy herding is possible (and hence sell herding is impossible), a marginal reduction in $P(V_3)$ would result in a *decrease* in buy herding intensity, whereas sell herding intensity would remain constant at 0. Similarly, if sell herding is possible for a given model parameterization (and buy herding impossible), a marginal reduction in $P(V_3)$ would result in an *increase* in sell herding intensity while buy herding intensity would remain unaffected. This converse effect on buy and sell herding intensity is due to the fact that a reduction in $P(V_3)$ diminishes the probability of buy-dominated trade histories and increases the probability of sell-dominated histories. Hence, potential sell (buy) herders are more (less) likely to be confronted with a trade history that sways them into herding. Second, if the U-shaped signal is positively biased, i.e., $P(S_2 \mid V_1) < P(S_2 \mid V_3)$, a reduction of $P(V_3)$ diminishes the number of U-shaped traders in the market and, hence, tends to decrease buy as well as sell herding intensity. Finally, for a whole range of model parameterizations, a lower $E[V]$ may even contribute to an increase in buy herding intensity and a decrease in sell herding intensity. Since a lower $E[V]$ implies that more informed traders are initially inclined to sell, the number of potential sell herders declines. Correspondingly, buy herding becomes more likely.

[9] Note that an increase in $\mathrm{Var}(V)$ may reduce the number of U-shaped traders in the market. This effect is not necessarily offset by an increase in IU. One could circumvent this issue by additionally imposing that the total probability that an informed trader receives a U-shaped signal $P(S_2) = \sum_{j=1}^{3} p^{2j} P(V = V_j)$ must also be high in times of market stress. Since this does not affect the results of our simulation, we choose not to complicate the model by adding this characteristic to the uncertainty definition.

These complex and partly counteracting effects, in conjunction with the history-dependent updating of beliefs, lead to a low analytical tractability of herding intensity in the Park and Sabourian (2011) model, see the Appendix. This particularly applies to the empirically relevant case where herding intensity is considered as an average over a set of stocks with heterogeneous characteristics. In the following, therefore, empirically testable predictions about the effects of information risk and market stress on average herding intensity are derived by numerically simulating the model over a broad set of model parameterizations.

3 Simulation of the Herd Model for a Heterogeneous Stock Index

3.1 Average Herding Intensity

Empirical studies on herd behavior typically derive results for herding intensity as an average for a large set of stocks and over certain time intervals. The stocks under consideration are likely to differ in their characteristics implying 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. In accordance with the empirical literature, we are particularly interested in herding intensity defined as an *average* over a broad range of model parameterizations that reflects the heterogeneity in stock market indices. Specifically, we define average herding intensity as follows:

Definition 3: *Average Herding Intensity*
For a given set of model parameterizations $\mathcal{I}$ and length T of the trading period, average buy herding intensity is defined as

$$\overline{BHI} = \frac{\sum_{i \in \mathcal{I}} w_i BHI_i}{\sum_{i \in \mathcal{I}} w_i},$$

where BHI_i stands for the buy herding intensity obtained for model parameterization i and the weights $w_i = b^{in}_{T,i} + s^{in}_{T,i}$ correspond to the number of informed trades observed for that parameterization.
The definition for average sell herding intensity $\overline{SHI}$ follows analogously.

Weights w_i ensure that average herding intensity is not biased upward by simulation outcomes with a low number of informed trades.[10]

3.2 The Simulation Setup

We choose μ, the fraction of informed traders, from

$$\mathcal{M} = \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}.$$

Accordingly, we simulate the model for $|\mathcal{M}| = 9$ different levels of information risk. In the German stock market, the share of institutional (i.e. informed) trading for the sample period ranges from 0.2 to 0.7, compare Kremer and Nautz (2013a).

The prior distribution of the risky asset $P(V)$ is chosen from

$$\mathcal{P} = \{P(V) \in \{0.1, 0.2, \ldots, 0.9\}^3 : \sum_{i=1}^{3} P(V_i) = 1\}.$$

Since we impose that V takes each value $V_1 = 0, V_2 = 1, V_3 = 2$ with positive probability, $P(V_i)$ cannot be 0.9, which gives us $|\mathcal{P}| = 36$ different prior distributions.

The conditional signal distribution $P(S|V) = (p^{ij})_{i,j=1,2,3}$ has to be chosen from the space of leftstochastic 3-by-3 matrices. As before, we discretize this space by

[10] Consider, for example, a situation where we observe a herding intensity of 0.5 as 2 out of 4 informed trades are herd trades. Now assume that for another simulation the herding intensity is 0 as 0 out of 16 informed trades are herd trades. In this case, the *unweighted* average of simulated herding intensities would be 0.25, which overestimates herding intensity as only 2 out of 20 trades were herd trades across the whole sample.

imposing a grid ranging from 0.1 to 0.9. All elements of $P(S|V)$ are positive, that is, all signals are noisy in the sense that an informed trader cannot with certainty rule out any of the three possible states for V. Following Park and Sabourian (2011), there are always optimists ($p^{31} < p^{32} < p^{33}$), pessimists ($p^{11} > p^{12} > p^{13}$), and U-shaped ($p^{21} > p^{22}, p^{22} < p^{23}$) traders in the market, see Section 2.1. Finally, informed traders tend to be well-informed, that is, if the bad state $V = V_1$ realizes, most of the informed traders will be pessimistic and few are optimistic ($p^{11} > p^{21} > p^{31}$) and vice versa for $V = V_3$ ($p^{13} < p^{23} < p^{33}$). This implies that the set of simulated signal structures ($\mathcal{C}$) can be summarized as follows:

$$\begin{aligned}
\mathcal{C} \quad = \quad & \{P(S|V) = (p^{ij})_{i,j=1,2,3} \text{ leftstochastic}: \ p^{ij} \in \{0.1, 0.2, \ldots, 0.9\}, \\
& p^{11} > p^{21} > p^{31}, \ p^{13} < p^{23} < p^{33}, \\
& p^{11} > p^{12} > p^{13}, \ p^{31} < p^{32} < p^{33}, \ p^{21} > p^{22}, \ p^{22} < p^{23}, \},
\end{aligned}$$

which leads to $|\mathcal{C}| = 41$ different signal structures used in the simulation.

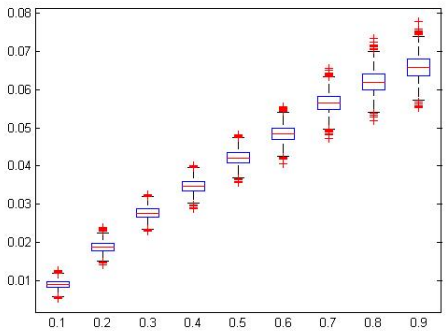
Considering all combinations, one obtains the simulation set $\Omega := \mathcal{M} \times \mathcal{P} \times \mathcal{C}$, where $|\Omega| = 9 \cdot 36 \cdot 41 = 13284$. Each element $\omega = (\mu, P(V), P(S|V)) \in \Omega$ describes the characteristics of a specific stock.[11] Park and Sabourian (2011) derive upper bounds for μ that have to hold in order for herding to be possible. One can check that these upper bounds are never binding for $\omega \in \Omega$, i.e. in each of the following simulations, either sell or buy herding is possible (see Park and Sabourian (2011), pp. 991-992, 1011-1012). Each stock is traded over $T = 100$ points of time. For each stock, the simulation is repeated $2,000$ times which produces more than 2.6 billion simulated trades for analysis.[12]

[11] In practice, stock characteristics ω may not be constant over time. For example, the Deutsche Bank share before the financial crisis is likely to have different characteristics than the Deutsche Bank share during the crisis.

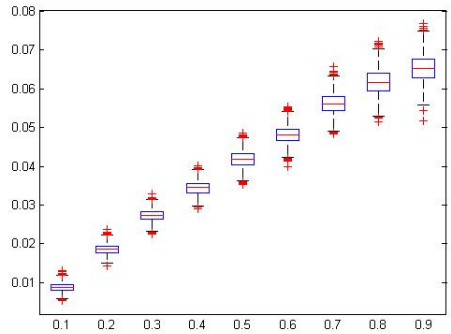
[12] Matlab codes are available on request.

Figure 1: Information risk and herding intensity

(a) Sell Herding



(b) Buy Herding



Notes: $\overline{SHI}$ and $\overline{BHI}$ are plotted against information risk. On the ordinate we plot average herding intensity. Information risk μ is plotted along the horizontal. Average herding intensity is calculated as the weighted cross-sectional average for the simulated $\overline{SHI}$ and $\overline{BHI}$ of stocks contained in $\{\mu\} \times \mathcal{P} \times \mathcal{C}$. The weights correspond to the observed number of informed trades. The boxplots show the variation across 2,000 simulations of average herding intensity for a fixed level of information risk μ.

3.3 Simulation Results: Information Risk and Average Herding Intensity

To discover the impact of information risk on average herding intensity, we fix $\mu \in \mathcal{M}$ and calculate average herding intensity as the cross-sectional average over all parameterizations in $\{\mu\} \times \mathcal{P} \times \mathcal{C}$, where $|\{\mu\} \times \mathcal{P} \times \mathcal{C}| = 1 \cdot 36 \cdot 41 = 1,476$.

Figure 1 shows the comparative statics for average sell and buy herding intensity with respect to changes in information risk μ. The simulation results clearly indicate that $\overline{SHI}$ and $\overline{BHI}$ symmetrically increase with information risk. The boxplots demonstrate that the simulation results are very stable. Indeed, the variation of average herding intensity for a given level of information risk is relatively low, whereas its increase is rather steep as μ goes up. This particularly applies to the empirically relevant range of $\mu \in [0.2, 0.7]$. Only as μ approaches 1, do $\overline{SHI}$ and $\overline{BHI}$ level out and exhibit higher variations.

The model simulation shows that the increasing effects of a rise in information risk on herding intensity dominate the decreasing effects. Only as the share of informed traders surpasses 80%, does the adverse selection problem of the market maker begin to impair market liquidity severely enough that trading among the potential herders breaks down. The ambiguity of their signal prevents them from paying the high premiums now demanded by the market maker via large bid-ask spreads. We summarize the simulation-based insight from Figure 1 as follows:

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

3.4 Simulation Results: Market Stress and Average Herding Intensity

For the analysis of the effects of market stress we define two distinct classes of stocks and compare the average herding intensity of each. The first class comprises all stocks that have high market stress characteristics; the second class all stocks that show low market stress characteristics. In line with the definition of market stress developed in Section 2.3.2, a simulated stock $\omega \in \Omega$ is subject to high market stress if it exhibits both above-average uncertainty and below average $E[V]$. Correspondingly, low market stress stocks are defined by below-average uncertainty and above-average $E[V]$. The averages are the respective medians of the simulated model parameterizations.[13] We compare the cross-sectional average $\overline{SHI}$ and $\overline{BHI}$ over all high market stress stocks with the $\overline{SHI}$ and $\overline{BHI}$ obtained for all low market stress stocks.

The simulation results for the impact of market stress on average sell and buy herding intensity are shown in Table 1. As expected, both sell and buy herding are

[13]Specifically, we obtain the median degree of pessimism (public uncertainty) by calculating $E[V]$ ($\mathrm{Var}(V)$) for each of the 36 simulated prior distributions $P(V) \in \mathcal{P}$ and then determine their median. Correspondingly, we calculate the median informed uncertainty over the set of simulated signal structures $\mathcal{C}$.

Table 1: The effects of market stress on average herding intensity

	$\overline{SHI}$	$\overline{BHI}$
Low market stress	0.0351 (0.0029)	0.0306 (0.0020)
High market stress	0.0382 (0.0023)	0.0635 (0.0038)

Notes: This table reports the simulated average sell ($\overline{SHI}$) and buy herding intensity ($\overline{BHI}$) for stocks under high market stress and stocks under low market stress. Standard deviations are in parentheses. Welch's t-test reveals that $\overline{SHI}$ as well as $\overline{BHI}$ increase significantly during times of high market stress for usual significance levels. Out of the 13,284 simulated stocks, 1,368 classify as high market stress and 1,008 as low market stress. Average herding intensities are calculated as the weighted cross-sectional averages of the simulated SHI and BHI for stocks in each respective class. The figures in the table are the weighted average and the weighted standard deviation of 2,000 iid simulated outcomes of $\overline{SHI}$ and $\overline{BHI}$ under high and low market stress, respectively. For all calculations, the weights correspond to the observed number of informed trades.

more pronounced during times of high market stress. Interestingly, however, the rise in buy herding intensity is greater than that of sell herding intensity. This puzzling asymmetry can be explained by disentangling the effects of an increase in uncertainty and pessimism.

Table 2 shows that $\overline{SHI}$ and $\overline{BHI}$ symmetrically increase with uncertainty. High public uncertainty is associated with lower prior probabilities for the middle state of the risky asset. Since informed traders receiving U-shaped signals discount the probability for the middle state anyway, high public uncertainty amplifies their tendency to form strong beliefs that only the extreme states of the risky asset can be true. As they rule out one of the extreme states based on the observed trading history, they quickly alter their trading decisions toward that of the crowd. This effect is intensified if private uncertainty is also high since such leads to a larger share of U-shaped traders. Since this argument applies equally to sell and buy herding, the increasing effect of uncertainty on herding intensity is symmetric.

In contrast, Table 3 reveals, that a reduction in $E[V]$ affects $\overline{SHI}$ and $\overline{BHI}$ in opposite ways. While increased pessimism contributes to buy herding, it significantly

Table 2: The effects of uncertainty on average herding intensity

	$\overline{SHI}$	$\overline{BHI}$
Low uncertainty	0.0373 (0.0018)	0.0340 (0.0016)
High uncertainty	0.0557 (0.0022)	0.0555 (0.0022)

Notes: This table reports the simulated $\overline{SHI}$ and $\overline{BHI}$ for stocks with high and low uncertainty respectively. Standard deviations are in parentheses. Welch's t-test reveals that $\overline{SHI}$ as well as $\overline{BHI}$ increase significantly during times of high uncertainty for usual significance levels. Out of the 13,284 simulated stocks, 3,078 exhibit high and, 2,268 low, uncertainty. Average herding intensities are calculated as the weighted cross-sectional averages of the simulated SHI and BHI for stocks in each respective class. The figures in the table are the weighted average and the weighted standard deviation of 2,000 iid simulated outcomes of $\overline{SHI}$ and $\overline{BHI}$ under high and low uncertainty, respectively. For all calculations, the weights correspond to the observed number of informed trades.

reduces sell herding. This result is driven by the fact that during times of grim economic outlook, most informed traders sell anyway. Herd behavior, however, requires a trader to *alter* her initial trading decision. For *sell* herding to be possible, for instance, the trader has to be initially inclined to *buy* the asset. Only informed traders receiving U-shaped signals with strong biases toward the high state of the risky asset (i.e., $p^{21} << p^{23}$) may still be inclined to buy initially for low $E[V]$. As $E[V]$ drops, so does the number of simulated signal structures in $\mathcal{C}$ that exhibit a sufficiently strong positive bias of the U-shaped trader for sell herding to be possible. By the same line of reasoning, $\overline{BHI}$ increases with low $E[V]$. We emphasize that the results in Table 3 do not contradict strong accumulations of traders on the sell side during times of deteriorated economic outlook. The Park and Sabourian (2011) model predicts that such a consensus in trade behavior is not driven by a switch in traders' opinion toward that of the crowd but is due to a high share of equally pessimistic traders all acting on similar information. Such correlation of trade behavior is called spurious or unintentional herding in the literature, compare e.g. Kremer and Nautz (2013a) and Hirshleifer and Hong Teoh (2003).

The simulation shows that the positive effect of increased uncertainty on sell herding

Table 3: The effects of economic outlook on average herding intensity

	$\overline{SHI}$	$\overline{BHI}$
High $E[V]$	0.0502 (0.0010)	0.0357 (0.0010)
Low $E[V]$	0.0370 (0.0016)	0.0504 (0.0016)

Notes: This table reports the simulated $\overline{SHI}$ and $\overline{BHI}$ for stocks where traders show high and low degrees of pessimism respectively. Standard deviations are in parentheses. Welch's t-test reveals a highly asymmetric effect for sell and buy herding. Indeed, $\overline{SHI}$ decreases as pessimism increases while $\overline{BHI}$ increases with the degree of pessimism. The results are significant at all usual significance levels. Out of the 13,284 simulated stocks, 5,904 stocks exhibit high and low degrees of pessimism. Average herding intensities are calculated as the weighted cross-sectional averages of the simulated SHI and BHI for stocks in each respective class. The figures in the table are the weighted average and the weighted standard deviation of 2,000 iid simulated outcomes of $\overline{SHI}$ and $\overline{BHI}$ under high and low uncertainty, respectively. For all calculations, the weights correspond to the observed number of informed trades.

dominates the negative effect of increased pessimism. This leads to an overall slight increase in $\overline{SHI}$ during times of high market stress. In contrast, the complementary effect of uncertainty and pessimism on buy herding results in a surge of $\overline{BHI}$ during times of high market stress. We consolidate these simulation results in the following

Hypothesis 2: Herding Intensity and Market Stress *In times of high market stress, the increase in buy herding is more pronounced than that of sell herding.*

4 Empirical Herding Measure

Simulating a herd model allows us to determine for each trade whether herding actually occurred. As a result, the exact herding intensity can be calculated for each model simulation. In an empirical application, it is much more difficult to decide whether or not a trader herds since researchers have no access to private signals.

The dynamic herding measure proposed by Sias (2004) is designed to explore

whether (institutional) investors follow each others' trades by examining the correlation between the traders' buying tendency over time. The Sias herding measure, therefore, is particularly appropriate for high-frequency 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} institutions are net buyers of 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. In the second step, the Sias measure for herding intensity is calculated as the time-series average of the estimated coefficients: $Sias = \frac{\sum_{t=2}^{T} \beta_t}{T-1}$.

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 equal to 1 if institution n is a buyer in i at time t and 0 otherwise. $D_{mi,t-1}$ is a dummy variable equal to 1 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. A positive correlation that results from institutions following other institutions, that is, the latter part of the decomposed correlation, can be regarded as evidence of herd behavior. In the subsequent empirical analysis, we 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" ($br_{i,t-1} > 0.5$) and "sell herding" ($br_{i,t-1} < 0.5$).

5 Empirical Results

5.1 Data

The data are from 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 that trade on an organized market. These records make it possible to identify all relevant trade characteristics, including the trader (the institution), the particular stock, time, number of traded shares, price, and the volume of the transaction. Moreover, the records specify on whose behalf the trade was executed, that is, whether the institution traded for its own account or on behalf of a client that is not a financial institution. Only institutions that fall under Section 9 of the German Securities Trading Act are allowed to submit trade orders to German trading platforms. Therefore, the data are a comprehensive repository of *all* trades executed on German stock exchanges

during the sample period. Since this study is concerned with institutional trades, particularly those of financial institutions, we restrict our attention to the trading of own accounts, that is, those cases where a bank or financial services institution is clearly the originator of the trade. We exclude institutions trading exclusively for the purpose of market making. We also exclude institutions that are formally mandated as designated sponsors, i.e., liquidity providers, for a specific stock. For each stock, there are usually about two institutions formally mandated as market maker. The institutions are not completely dropped from the sample (unless they have already been excluded due to engaging in purely market maker business), but only for those stocks for which they act as designated sponsors.[14] We are particularly interested in the herding behavior of institutional investors because they are more likely to be informed compared to, for example, retail investors. 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 analysis focuses on shares listed on the DAX 30 (the index of the 30 largest and most liquid stocks), where stocks are selected according to the index compositions at the end of the observation period on March 31, 2009. Following the empirical literature, we require that at least five institutions were active in the market at each trading interval. Using data from July 2006 to March 2009 (698 trading days), we are able to investigate whether trading behavior has changed during the financial crisis. Over the sample period, there are 1,120 institutions engaging in proprietary transactions. Among those 1,120 traders, 1,044 trade on the DAX 30 stocks.

[14]The designated sponsors for each stock are published at http://www.deutsche-boerse.com. For more information about the data, see Kremer and Nautz (2013a,b).

5.2 Information Risk and Herding Intensity in the German Stock Market

The higher the number of informed traders active in a market, the higher the probability of informed trading and, thus, information risk. According to Hypothesis 1, average herding intensity increases with information risk, reflected in the parameter μ, the fraction of informed traders. In the following, we use 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 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. 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.[15] The first two columns of Table 4 show how both empirical proxies for information risk are distributed within a day. For both measures of trading activity, institutional traders are more active during the opening and closing intervals.

To investigate the intra-day pattern of herding intensity, we calculate the Sias herding measure for each half-hour interval separately. The results of this exercise are also shown in Table 4. 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)). Following Sias (2004), this correlation may overstate the true herding intensity because it does not account for correlation resulting from traders who follow themselves. It is a distinguishing feature of our investor-specific data that they allow addressing that problem even on an intra-day basis. In particular, Column 4 reports

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

Table 4: 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. *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 occured between 9 a.m. and 9:30 a.m. The columns do not add to 1 because we focus on the predominant German platform Xetra®, where trading takes place from 9 a.m. till 5.30 p.m. CET, while the opening period for the German stock exchange at the floor ends at 8 p.m. *Sias* and $\overline{Sias}$ represent the overall and the adjusted Sias herding measure (in percent), where the latter only considers institutions that follow the trades of others, see Equation (3). Standard errors are in parentheses.

the correlation due to investors following the trades of others ($\overline{Sias}$) (see Equation (3)).

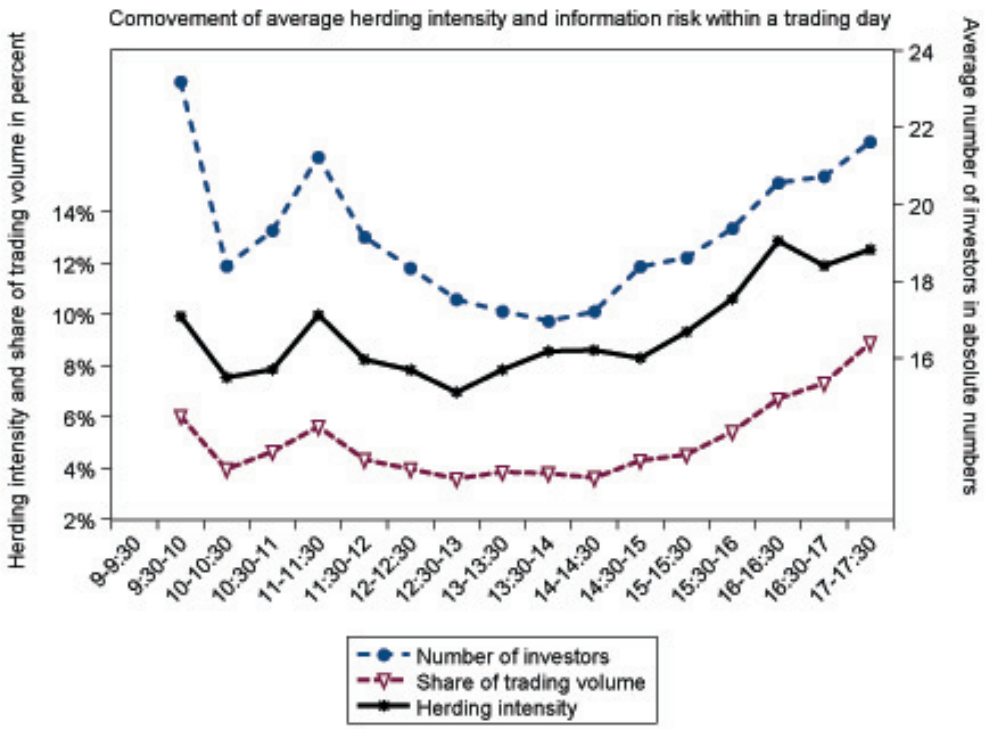
Table 4 offers several insights into the intra-day pattern of institutional herding. First, both Sias measures provide strong evidence for the presence of herding for each half-hour interval of the trading day. Second, intra-day herding measures are significantly larger than those obtained with low-frequency data, compare Kremer and Nautz (2013a,b). Third, the sizable differences between $Sias$ and $\overline{Sias}$ highlight the importance of using investor-specific data.

How is the observed intra-day variation of information risk related to the intra-day herding intensity of institutional investors? In line with the intuition of Park and Sabourian (2011), the Sias herding measure depends on the trading behavior in two subsequent time periods. 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. Therefore, for each time interval herding intensity is compared with the average information risk of the corresponding time intervals. Figure 2 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 rank-correlation coefficient between the average trading volume and the corresponding Sias measure is 0.80, which is both economically and statistically highly significant. Very similar results are obtained for the number of active institutional traders, where the correlation coefficient equals 0.67.[16]

Note that the peaks in $\overline{Sias}$ at market opening and following the opening of the U.S. market at 3:30 p.m. – 4 p.m. correspond with high activity by informed traders, suggesting that at market openings there is a lot of information contained in observed

[16]These results can be confirmed using standard correlation coefficients, which are also large and significant at all conventional levels for both empirical proxies of information risk. 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).

Figure 2: Information Risk and Average Herding Intensity within a Trading Day



trades on which subsequent traders herd. This confirms the experimental findings of Park and Sgroi (2012), who observe that traders with relatively strong signals trade first, while potential herders delay.

5.3 Herding Intensity in the German Stock Market Before and During the Financial Crisis

According to Hypothesis 2, both sell and buy herding should increase in times of high market stress when uncertainty increases and markets become more pessimistic about the value of the asset. However, the increase in sell herding is predicted to be smaller than the one in buy herding. In our application, a natural candidate to test this hypothesis is the outbreak of the financial crisis. To investigate the effect of the crisis

Table 5: 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 buy and sell herding components (see Section 4). Standard errors are in parentheses.

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 to be 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 5. The results confirm the predictions of the simulated model. The statistically significant yet small increase in sell herding ($5.74 > 5.41$) is well in line with Hypothesis 2 as is the more pronounced surge in buy herding ($5.09 > 4.10$).

Apparently, in times of deteriorated economic outlook when traders are exposed to recurring bad news, a small but unexpected accumulation on the buy side is quickly interpreted as good news about an asset's value and induces investors to follow the crowd (as small as it may be) into the alleged investment opportunity. Such behavior—in light of Hypothesis 2—is by no means purely based on investor sentiment or irrationality, but may be perfectly rational. In line with our theoretical results, the increase in sell

herding during the crisis period indicates that the high uncertainty effect dominates the low expectation effect discussed in Section 3. The increase, however, may also be explained by reasons outside the model. If asset prices start to fall, selling may become necessary in order for institutional traders to meet regulatory requirements. The resulting accumulation of institutional traders on the sell side of the market may upward bias the sell herding intensity detected by the empirical herding measure. Yet, the small increase in sell herding intensity in the German stock market during the crisis period indicates that these diluting effects of unintentional herding are not of particular relevance for our sample.

6 Concluding Remarks

Due to data limitations and a lack of testable, model-based predictions, the theoretical and the empirical herding literature are only loosely connected. This paper contributes tightening this connection. First, we derive theory-based predictions regarding the impact of information risk and market stress on herding intensity by numerically simulating the financial market herd model of Park and Sabourian (2011). We then test these predictions empirically using a comprehensive data set from the German stock market. As predicted by the model, we find that both buy and sell herding increase symmetrically with information risk. Our empirical results further show that the herd model can explain why buy and sell herding in the German stock market evolve asymmetrically in response to increased market stress induced by the financial crisis.

There are several interesting avenues for future research that will aid in further tightening the connection between the theoretical and empirical herding literature. For example, during crises periods, correlation across assets and contagious effects may play an important role in explaining investor behavior. Herd models, however, are typically single-asset models and are not designed to provide insights regarding herd intensity in a context of correlated assets and informational spillovers. Therefore, an

extension of herd models to a multiple asset setting would facilitate the interpretation of evidence based on aggregate herding measures. A second suggestion involves the design of empirical herding measures. The prevailing measures assess correlated trade behavior (see, e.g., Lakonishok et al. (1992), Sias (2004), Patterson and Sharma (2010)) and thus are able to detect the accumulation of investors on one side of the market. However, these measures do not reveal whether this consensus in trade behavior is actually due to true herding, that is, whether it is due to traders ignoring their private information and instead copying the behavior of others. As a result, correlated trading indicated by empirical herding measures is not necessarily a sign of inefficiency but could be a joint reaction to the same information or due to the use of similar risk models, see Kremer and Nautz (2013a). More work is needed to further our understanding to what extent and under which circumstances empirical herding measures actually detect true herding as understood by the theoretical literature.

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A The History Dependence of Herding Intensity

Financial market herd models, including the model of Park and Sabourian (2011) , are not designed to provide closed-form solutions for expected herding intensity. In this appendix, we use two examples to demonstrate why numerical simulations are required for obtaining model-based results regarding the impact of information risk and market stress on herding intensity.

Even for a given model parameterization, model complexity prevents deriving a closed-form analytical formula for herding intensity. The herding definition depends on the market maker's quotes, ask_t and bid_t, as well as the informed traders' expectations regarding the asset's true value $E[V \mid S, H_t]$. These quantities, in turn, depend on the whole history of trades until t. In fact, not only the number of observed buys, sells and holds but also their order affects expectations and quotes at time t. As a consequence, even for a given model parameterization, each history path would need to be analyzed separately to derive results on expected herding intensity.[17]

Let us illustrate this issue with a concrete numerical example. Assume the conditional signal matrix $P(S \mid V)$ to be

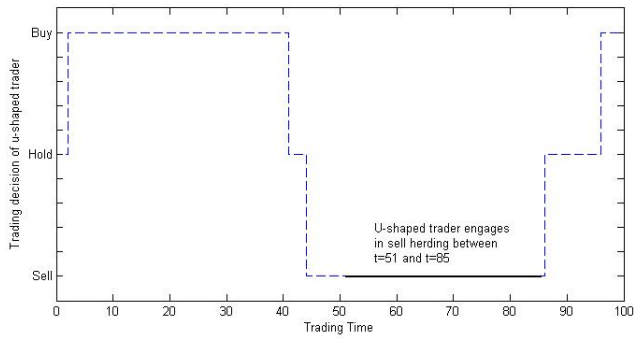
$P(S \mid V)$	$V_1 = 0$	$V_2 = 1$	$V_3 = 2$
S_1	0.6	0.5	0.1
S_2	0.3	0.1	0.4
S_3	0.1	0.4	0.5

The distribution of the risky asset is $P(V) = [0.3\ 0.4\ 0.3]$. Multiplying $P(S \mid V) \cdot P(V)$ yields the unconditional probabilities $P(S) = [0.41\ 0.25\ 0.34]$ that a trader receives a signal S given that she is informed. Finally, the share of informed traders is set

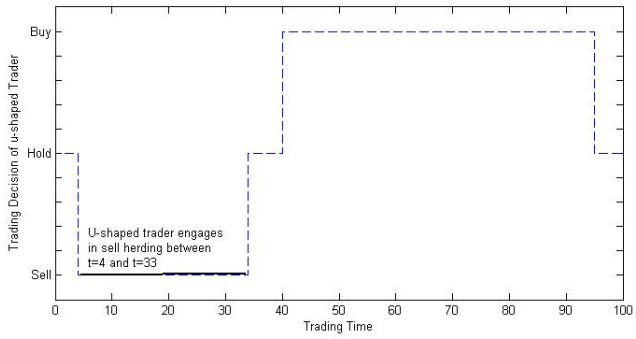
[17] Given the sheer number of possible trading histories alone, an analytical derivation of SHI and BHI is not feasible even for relatively small T. For any length T of the history H_T, there are 3^T different history paths.

Figure 3: Trading decisions of U-shaped trader for $\mu = 0.5$

(a) $H_1^{100} = \{25\ buys,\ 50\ sells,\ 25\ buys\}$



(b) $H_2^{100} = \{25\ sells,\ 50\ buys,\ 25\ sells\}$



to be $\mu = 0.5$. Only informed traders receiving the U-shaped signal S_2 can herd. Given that $E[V] = 1 < 1.12 = E[V \mid S_2]$, the U-shaped trader can engage in sell herding only if she is inclined to buy initially.[18] We discuss two distinct trading histories consisting of 100 trades and the exact same number of buys and sells. The only difference is the order in which the trades are observed. Let $H_1^{100} = \{25\ buys,\ 50\ sells,\ 25\ buys\}$ and $H_2^{100} = \{25\ sells,\ 50\ buys,\ 25\ sells\}$. Figure 3 shows how a U-shaped trader would decide to trade at every time $t = 1, ..., 100$ for the respective trading histories.

[18]Note that S_2 holds initially as the ask price $ask_0 = 1.18$ quoted by the market maker prevents S_2 from buying.

Note that the number of trades for which S_2 sell herds differs for the two histories. Under H_1^{100}, S_2 potentially sell herds between periods 51 and 85, i.e. 35 times.[19] Under H_2^{100}, S_2 potentially sell herds only 30 times. The share of U-shaped traders among the population of all traders is $\mu P(S_2) = 0.5 \cdot 0.25 = 0.125$. Consequently, we expect to observe a total number of $s_{T,1}^h = 0.125 \cdot 35 = 4.375$ herding sells under $H1^{100}$. Correspondingly, under H_2^{100}, we only have $s_{T,2}^h = 0.125 \cdot 30 = 3.75$ expected herd sells. Furthermore, since $\mu = 0.5$ and $T = 100$, we expect that both histories contain 50 informed trades.[20] According to Definition 2.2, the sell herding intensity is $SHI = s_T^h / b_T^{in} + s_T^{in}$. Plugging in the expected values for numerator and denominator that we just calculated, we obtain an expected sell herding intensity $SHI_1 = 4.375/50 = 0.0875$ under H_1^{100} and $SHI_2 = 3.75/50 = 0.75$ under H_2^{100}.[21] Finally note that the probability of observing these histories $P(H_i^{100})$ is also different for $i = 1, 2$, since the probability of observing a certain trade (i.e., buy or sell) in t depends on the trading decisions of the informed traders at t. This means, that in order to calculate an overall expected herding intensity for the model parameterization above, we would need to analyze SHI and $P(H^{100})$ for all 3^{100} possible history paths separately, a task well beyond our current computational capacity. Even if we were able to calculate that number, we still would not have a formula that tells us how SHI would react to changes in certain model parameters such as μ. Indeed, one can illustrate the many counteracting effects of a change in μ that result in quite different outcomes for specific trading histories and thus also prevent the derivation of analytical comparative static results.[22]

[19] Note that S_2 does in fact start herding only in period 51, although she would already have decided to sell in period 44. This is because the complete history does not contain more sells than buys until period 51, which we demand in order to ensure that S_2 actually follows the majority in the market.

[20] Note that for an arbitrary history, calculation of the expected number of informed trades is much less straight forward since there is the possibility that informed traders hold and we hence have fewer informed trades than 50. Since H_1^{100} and H_2^{100} do not contain any holds, however, this is not an issue here.

[21] Note, that since numerator and denominator are clearly correlated, we have that $E[\frac{X}{Y}] \neq \frac{E[X]}{E[Y]}$. A Taylor approximation of order 1, however, yields that the expectation of a ratio can be consistently estimated by the ratio of the expectations. As a consequence, all equations should be understood as approximations. An exact calculation of expected herding intensity would be even more complicated.

[22] A numerical example how an increase in μ would affect SHI for the above trading histories is available on request or in our working paper version.

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