Correlated Trades and Herd Behavior in the Stock Market: Empirical Results from an Intra-Day Analysis

Preliminary Version

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Abstract

Herd behavior is often viewed as a significant threat for the stability and efficiency of financial markets. This paper sheds new light on the relevance of herd behavior for observed correlation of trades. We introduce numerical simulations of a herd model to derive theory-guided predictions regarding the impact of various aspects of uncertainty on herding intensity. We test the predictions using a novel data set including all real-time transactions of institutional investors in the German stock market. In light of our simulation results, the observed correlation of trades is mainly due to the common reaction of investors to new public information and should not be misinterpreted as herd behavior.

Keywords: Herd Behavior, Institutional Trading, Informational Cascades, Correlated Trading

JEL classification: G11, G24, C23

1 Introduction

Correlated trading of institutional investors is a widely discussed empirical phenomenon, in particular the rationale behind correlated trading remains an open issue. On the one hand, correlated trading can occur unintentionally as investors react commonly on the same public information. On the other hand, correlated trading can be the result of herd behavior. Herding investors ignore their own noisy information and intentionally follow other market participants, since they infer from observed trading behavior that others have relevant information. Therefore, correlated trading induced by herd behavior impedes the informational efficiency of financial markets with possibly destabilizing consequences, see, e.g., Lee (1998). This paper tries to shed more light on the relevance of herd behavior for the observed correlation of trades from both a theoretical and an empirical perspective. In a first step, we perform numerical simulations of a herding model to derive theory-guided predictions regarding the role of various aspects of uncertainty for market-wide herding. In a second step, the predictions are tested empirically using a comprehensive data set of the German stock exchange.

Herding models show how herd behavior can arise under certain market conditions that are characterized by e.g. the precision of private signals, compare Avery and Zemsky (1998) and Park and Sabourian (2011).[1] It is less clear, however, what determines one market to be more prone to herd behavior than another. For example, in Avery and Zemsky (1998), even the sign of the effect of more informative signals on herding intensity depends on the complete model parameterization.

The empirical content of herding models is further complicated by the fact that model parameters cannot be expected to be constant over time and across stocks. Nevertheless, empirical herding measures are typically based on the average correlation of trades observed under heterogenous market conditions in a broad range of stocks. In order to

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[1] Further aspects of market conditions discussed in the theoretical literature are transaction costs (Lee (1998)), endogenous sequencing of trades (Chari and Kehoe (2004)), heterogenous risk aversion (Décamps and Lovo (2006)) and informational spillovers across different markets (Cipriani and Guarino (2008)).

capture the diversity of a broad stock market index, we derive results for the average herding intensity by solving the Avery and Zemsky (1998) herding model numerically for a wide range of parameter values. The results of this simulation exercise can be summarized by three testable hypotheses regarding the impact of market conditions on the degree of herding. First, herding should increase in times of market turbulence, particularly during the recent financial crisis. Second, herd behavior should decrease in times of a sudden inflow of new public information, for example during the opening intervals of financial markets. Third, and probably more surprising, the simulation suggests that herding intensity should be small when signals are noisy, e.g. when financial analysts' recommendations are disperse. Therefore, in contrast to the intuition of e.g. Patterson and Sharma (2010) and Chiang and Zheng (2010), increased uncertainty does not necessarily lead to increased herding.

Especially in developed markets, herd behavior should be more of an intra-day phenomenon because herds are stopped by the arrival of public information and consequent price adjustments will dominate information from observed behavior.[2] Therefore, an empirical analysis of herd behavior requires a fine-grade analysis of disaggregated investor-level data. Yet, the literature on institutional herding has been handicapped by the unavailability of appropriate data. The bulk of the empirical literature had to rely on institutions' changes in quarterly holdings which cannot account for the short-term character of informational cascades.

The empirical part of the paper contributes to the literature by analyzing intraday investor-level data that directly identify transactions by each trader. The data are provided by the German Federal Financial Supervisory Authority (BaFin) and include all real-time transactions in the major German stock index DAX 30 carried out by banks and financial services institutions. 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

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[2]Most herding models, including Avery and Zemsky (1998) and Park and Sabourian (2011), show that prices eventually converge to the fundamental values. In fact, our simulation results show that prices converge rather quickly.

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 intraday data before.[3]

Our empirical results confirm that transactions of financial institutions are correlated within a trading day, i.e. herding measures are found to be significant. However, in light of the theoretical predictions derived from the simulation exercise, the evidence does not support herd behavior as a major explanation for the correlated trading activity of institutional investors. First, we found only weak evidence for increased herding intensity during the crisis period. Second, in contrast to theoretical predictions, herding measures are significantly higher in the opening intervals and the afternoon session when new information enters into the German market due to the opening of the U.S. market. Third, herding intensity decreases only to a very small amount at days of high analyst dispersion.

The rest of the paper is structured as follows: Section 2 presents the herding model and the simulation setup used to derive testable hypotheses on the role of market conditions for herding intensity. Section 3 and 4 introduce the data and the empirical herding measure. Section 5 shows the empirical results. Section 6 offers some concluding remarks.

2 Herding in Financial Markets

The large literature on the causes and consequences of informational cascades and herd behavior was initiated by the seminal work of Bikhchandani et al. (1992) and Banerjee (1992).[4] In Bikhchandani et al. (1992) agents choose whether to invest in a project at fixed costs. Bayesian agents act sequentially and base their decision on

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[3]In a companion paper, Kremer and Nautz (2012) use this data set to demonstrate how empirical herding measures are affected by both the identification of traders and the underlying data frequency. Patterson and Sharma (2010) analyze herding in the U.S. market within an intra-day context using anonymous transaction data that does not allow to differentiate between traders.

[4]Comprehensive surveys of the theoretical and empirical herding literature are provided by Chamley (2004), Hirshleifer and Hong Teoh (2003) and Vives (2008).

a private noisy signal and the observed behavior of their predecessors. Both sources may present conflicting information. Bikhchandani et al. (1992) show that eventually agents disregard their private signals, with a positive probability that agents herd on the wrong side.

Avery and Zemsky (1998) adjust the basic herding model to the situation in financial markets. In particular, they abandon the assumption of fixed costs and introduce a market maker who incorporates all publicly available information in the prices. Interestingly, in this setup herding disappears because it is always optimal to trade based on private information. However, if the model is augmented by additional dimensions of uncertainty beyond the value of the asset and information disadvantages for the market maker, herding reemerges.[5]

Herding models emphasize the importance of uncertainty and asymmetric information for the trading behavior in financial markets. Yet, herding models are not designed to provide testable predictions about the effects of various aspects of uncertainty on the degree of herding.[6] In particular, from a theoretical perspective, it is far from obvious how herding intensity should be affected by i) market turbulences, ii) the expected arrival of new public information, or iii) the precision of private signals. In order to shed more light on these questions, we perform numerical model simulations to derive theory-guided predictions on the effects of market conditions on average herding intensity for a wide range of parameter values. The simulations is based on the herding model of Avery and Zemsky (1998) which provides an appealing way to parameterize the market conditions under investigation.

2.1 The herding model of Avery and Zemsky

In the following, we briefly review the Avery and Zemsky (1998) herding model, introduce the simulation setup and explain how certain model parameters can be linked to

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[5]Recently, Park and Sabourian (2011) showed that the distribution of signals plays an important role for herding to arise. In particular, signals need to be U-shaped, such that traders put more weight on the extremes of an asset's possible values.

[6]For example, Wermers (1999) and Sias (2004) investigate how firm size affect herding intensity.

market conditions in the German stock exchange. Avery and Zemsky (1998) charac-
terize a stock by the following four parameters: the probability of an information event
(α), the probability that a stock increases in value given an information event (δ), the
fraction of informed traders (μ), and the precision of an informed trader's signal (p).

The Asset: An asset with fundamental value $V \in \{0, 1/2, 1\}$ is traded over $t =
1, \ldots, T$ consecutive points in time. The probability that $V = 1/2$ is $1 - \alpha$ with
$\alpha \in (0, 1)$. The parameter α determines the probability of an information event. That
is, α should be high at the opening intervals of financial markets when a lot of new
information arrives.[7]

Given that $V \neq 1/2$, the probability that $V = 1$ is $\delta \in (0, 1)$. Thus, the larger δ, the
more optimistic is the market. Put differently, δ should be low during a financial crisis
period. Note that the model is symmetric in δ in the sense that herding intensity only
depends on $\Delta = |\delta - 1/2|$. In the simulation exercise, we therefore restrict the attention
to $\delta > 1/2$ without loss of generality.

The Traders: Traders arrive one at a time in a random exogenous order in the
market and decide to buy, sell or not trade one unit of the asset at the quoted bid
and ask prices. Traders are either informed or noise traders. The fraction of noise
traders is $1 - \mu$ and they decide to buy, sell or not to trade with equal probability.
Thus, noise traders ignore any information and cannot herd by definition. Informed
traders receive a private signal $S \in \{0, 1/2, 1\}$ on the fundamental value of the asset
and observe all publicly available information, i.e. all trades and posted prices up to
their arrival. They decide to 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 our empirical
application, we assume that institutional investors are informed traders.

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[7]Note that this testable prediction could not be derived within the framework of Park and Sabourian
(2011) since it does not allow to distinguish between information and non-information events.

The Private Signal: The signal is drawn from a distribution conditioned on the value of the asset, where $\Pr(S = v | V = v) = p \in (1/2, 1)$ if $v \neq 1/2$ and $\Pr(S = 1/2 | V = 1/2) = 1$. Accordingly, informed traders know whether $V \neq 1/2$, i.e. whether an information event occurred. In case of an information event, informed traders receive an imprecise private signal about the value of the asset, i.e. whether $V = 1$ or $V = 0$. The parameter p determines the precision of the signal: the larger p the more precise the signal. In our empirical application, we will assume that the precision of signals correlates with the distribution of the buy and sell recommendations of financial analysts.

The Market Maker: Trading takes place in interaction with a market maker who sets the bid and ask price. The market maker accesses only the public information and is subject to perfect competition such that he makes zero-expected profit. Thus, he sets the ask (sell) price equal to its expected value of the asset given a buy (sell) order and the public information.

2.2 The ambiguous effects of market conditions on herding intensity

Avery and Zemsky (1998) show that herd behavior can arise in this setup provided that private signals are sufficiently imprecise. Specifically, Avery and Zemsky (1998) derive a critical value for the precision of traders' signals, $\bar{p}$, for which herd behavior arises. Unfortunately, however, no general results are available that would provide straightforward predictions on the effect of changes in model parameters on the degree of herding. Let us illustrate this problem for the impact of variations in p, δ, and α.

In response to an increase in p, traders' signals are more informative about the fundamental value of the asset and it seems less likely that traders' decisions based on their private signals are overturned by the public information. However, this intuition might be misleading because public information increases as each of the preceding trades by informed traders carries more information. Therefore, the overall effect on the degree of herding is not obvious. A similar reasoning applies to the probability of an information

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event, α. On the one hand, if α decreases the market maker has stronger priors that $V = 1/2$. As a result, he will adjust prices more slowly into the direction of $V = 0$ or $V = 1$ with incoming buy or sell orders. In case of an actual information event this gives the informed traders an advantage in interpreting the preceding trades. As a consequence, herding is more likely to arise and long lasting. On the other hand, a decrease in α means that information events happen less often. As a result, stocks will experience less days where herd behavior could arise. Therefore, the overall effect of changes in α on the degree of herding is also ambiguous. Finally, consider the effects of an increase in $\Delta = |\delta - 1/2|$. On the one hand, an increase in Δ reduces uncertainty with respect to the value of the asset which should reduce the risk of herding. On the other hand, however, an increase in Δ also increases asymmetric information as the information advantage of informed traders over the market maker increases. Therefore, herding intensity may also increase.

Apparently, the effects of changes in a single model parameter on herding intensity are non-monotonic and related to the level of the remaining model parameters. In practice, the effect of, say, an increase in α may thus depend on the specific stock under consideration. Since the empirical herding literature focusses on the *average* amount of herding in a large and heterogenous stock market, theoretical predictions for the overall effect of market conditions on herding intensity are not clear. In view of these problems, we simulate the herding model for a broad range of parameters in order to derive theory-guided predictions on the role of i) market turbulence (Δ), ii) the availability of public information (α) and iii) the precision of signals (p) for the average degree of herding in a stock market.

2.3   The simulation exercise

Consider a heterogenous stock market $\Omega = M \times A \times D \times P$, where each stock $\omega_i \in \Omega$ is represented by the corresponding set of model parameters $\omega_i = (\mu_i, \alpha_i, \delta_i, p_i)$. In the following simulation exercise, we assume that the fraction of informed traders in stock i, μ_i, is taken from $M = \{0.2, 0.3, 0.4, 0.5, 0.6\}$ which corresponds to the range

of market shares of institutional investors observed for our sample period. α_i, the probability of an information event relevant for stock i, varies between 0.1 and 0.9, i.e. $A = \{0.1, 0.3, 0.5, 0.7, 0.9\}$ covering both low, medium, and high event probabilities. δ_i, the probability of $V_i = 1$ given an information event, ranges according to $D = \{0.55, 0.65, 0.75, 0.85, 0.95\}$, where the symmetry of the model around $\delta = 1/2$ allows us to focus on values of $\delta > 1/2$. Finally, p_i, the precision of the private signal, also varies according to $P = \{0.55, 0.65, 0.75, 0.85, 0.95\}$. In this case, restricting the attention to probabilities above 0.5 is plausible because $p_i < 0.5$ would imply that the signal is not only imprecise but even misleading on average.

Simulating the corresponding probability distributions, each stock $\omega_i = (\mu_i, \alpha_i, \delta_i, p_i)$ is traded over $T = 50$ periods. For each ω_i, the simulation is repeated 2000 times.[8] A trader engages in herd behavior if his action (buying or selling) corresponds to the action of the majority of the past traders and is independent of his private signal.[9] In empirical applications, it is difficult to decide whether a trader herds or not since researchers have no access to private signals. In contrast, this is not a problem in our simulation exercise where all model parameters are under control and the realizations of private signals are observable. We define herding intensity in stock ω_i as the fraction of informed traders that engage in herd behavior over the total number of informed buy and sell decisions during the 50 trading periods.[10] Accordingly, we obtain the degree of herding in the whole market as the average over all stocks and all 2000 repetitions. Due to the ambiguous effects of changes in p, α and δ on the degree of herding in the whole market, we are particularly interested in how the average herding intensity depends on these three parameters. Figure 1 to 3 summarize the simulation results obtained for the average herding intensity. In accordance with Park and Sabourian (2011), our simulation shows that the average herding intensity predicted by a stylized rational

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[8] We also ran the simulations with 500 and 1000 repetitions which showed that the results are robust.

[9] The formal definition of buy herding implemented in the simulation is as follows: A trader engages in buy herding at time t if and only if $V \neq 1/2$, $E[V|S = 0] \leq ask_t$, $E[V|H_t, S] > ask_t \ \forall S = 0, 1$ and $E[V|H_t] > E[V]$, where $E[\cdot]$ denotes the expectation operator, H_t denotes the history of trades, i.e. all trades up to time $t - 1$, and ask_t is the ask price at time t. The definition of sell herding is analogous. The matlab-codes for the model simulation are available upon request.

[10] Note that during 50 trading periods 16 buy or sell orders come from informed traders on average.

expectation model is rather small.

Figure 1: The Effect of δ on Herding
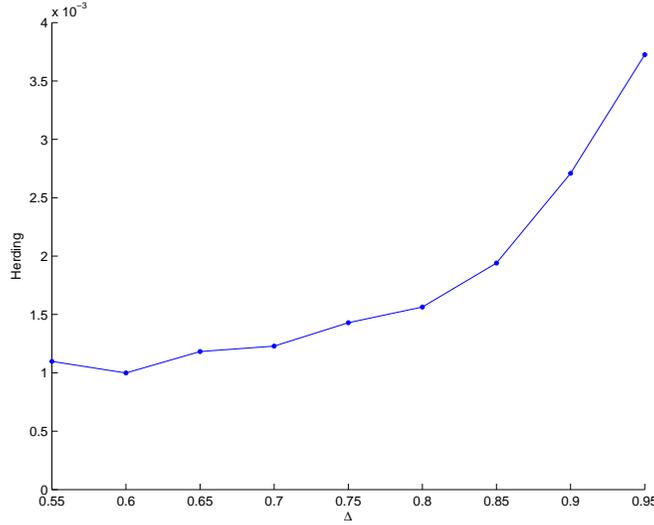
Notes: We construct $\Omega_i = M \times A \times \delta_i \times P$, where $\delta_i = 0.55 + 0.05(i-1)$ $(i = 1, 2, \ldots, 9)$. The figure plots the average herding intensity measured for each Ω_i against δ_i. δ denotes the probability that a stock increases in value given an information event. Low values for δ are, therefore, interpreted as times of market distress. Due to symmetry, we display the results for $\Delta_i = |\delta_i - 1/2|$.

Figure 1 shows that increases in $\Delta = |\delta - 1/2|$ tends to increase average herding intensity. This implies that herding increases in turbulent times when the probability that a stock either increases or decreases in value is very high. Provided that δ has decreased significantly below 0.5 since the outbreak of the financial crisis, it follows:

Hypothesis 1 (Herding in times of market turbulence). *Average herding intensity should have increased since the outbreak of the financial crisis.*

Figure 2 shows that the average herding intensity decreases with the probability of an information event α. While counteracting effects made general theoretical predictions difficult, the simulation exercise clearly demonstrates that the average herding intensity should be high if α, the inflow of new information, is low. Suppose that α, the probability of an information event, increases in times of a sudden inflow of new public information, e.g. at the opening intervals of financial markets. This leads us to the following testable hypothesis:

Figure 2: The Effect of α on Herding
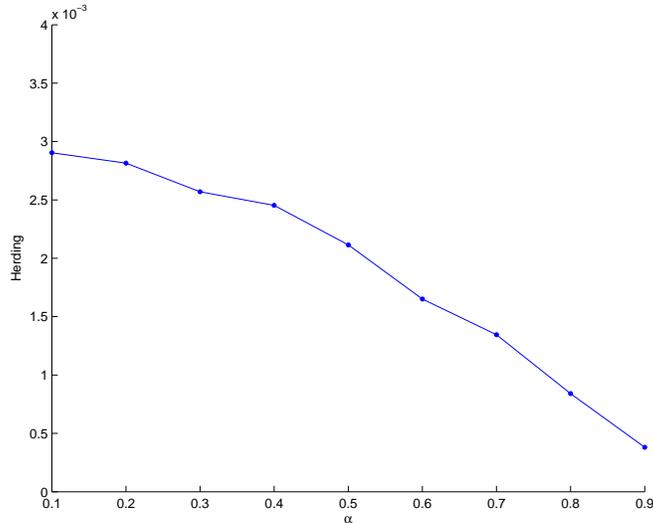
Notes: We construct $\Omega_j = M \times \alpha_j \times D \times P$, where $\alpha_j = 0.1j$ $(j = 1, 2, \ldots, 9)$. The figure plots the average herding intensity measured for each Ω_j against α_j. α denotes the probability of an information event, i.e. α should be particularly high at the opening intervals of financial markets.

Hypothesis 2 (Herding at the market opening). *Average herding intensity should be particularly low at the opening intervals of financial markets.*

In line with the non-monotonic effect of p on herding intensity, Figure 3 confirms that the empirical relationship between herding intensity and the precision of signals is more complicated. However, the simulation results suggest that herding intensity increases in the precision of signals as long as p is neither extremely high nor extremely low. Thus, one may expect that the average herding intensity decreases if the precision of signals decreases. In practice, the information content of signals should correlate with the dispersion of the recommendations of financial analysts. Specifically, if analysts' dispersion is high, the precision of signals should be low and *vice versa*, compare Brown et al. (2012) and Christoffersen and Tang (2009). This implies:

Hypothesis 3 (Herding and disagreement among financial analysts). *Average herding intensity should decrease when analysts' recommendations become more disperse.*

In the following section, we introduce the data set and the empirical herding measure

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Figure 3: The Effect of p on Herding
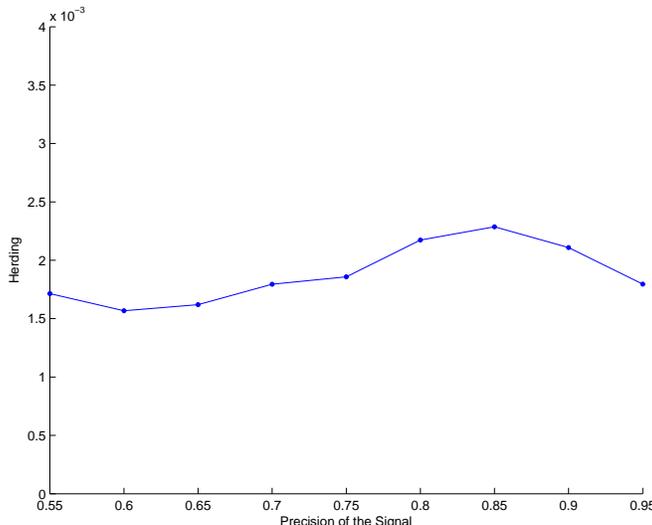
Notes: We construct $\Omega_k = M \times A \times D \times p_k$, where $p_k = 0.55 + 0.05(k-1)$ $(k = 1, 2, \ldots, 9)$. The figure plots the average herding intensity measured for each Ω_k against p_k. p denotes the precision of informed traders' signals. Assuming that the precision of signals correlates with the distribution of analysts' buy, sell and hold recommendations, p should be particularly low if analysts' recommendations are disperse.

that we employ to analyze the empirical content of these hypotheses.

3   The Data Set

The empirical part of the paper is based on disaggregated high-frequency investor-level 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.[11] These records allow for the identification of all relevant trade characteristics, including the trader (the institution). The information also include e.g. the particular stock, time, number of traded shares, price, and the volume of the transaction. Moreover, the records identify on whose behalf the trade was executed, i.e., whether the institution

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[11]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. In a companion paper, Kremer and Nautz (2012) use this data to show the impact of data-frequency on herding levels by comparing quarterly, monthly and daily calculations.

traded for its own account or on behalf of a client that is not a financial institution. Since the aim of our study is the investigation of institutional trades, particularly those of financial institutions, we focus on the trading of own accounts, i.e., those cases when a bank or a financial services institution is clearly the originator of the trade. 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.[12]

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. The market share of institutional investors during the observation period varied between about 20% to 60%. In order to estimate intra-day empirical herding measures, we divide each trading day into 18 intervals as displayed in Table 1. The opening period (9.00 a.m. to 5.30 p.m.) of the trading platform Xetra, where the bulk of trades occur, is divided in 17 half-hour intervals. The rest of the trading day (5.30 p.m. to 8.00 p.m.) is summarized to a final 18th period in order to ensure that there are always enough active institutions to perform an intra-day analysis. Table 1 reports summary statistics on the evolution of the intra-day trading activity of institutional investors. While traders are particularly active at the opening (about 25) and closing (22.5) intervals, the number of institutions trading appears to be rather stable throughout the day. The highest trading volumes are typically observed at the beginning (6.73%) and at the end of the day (about 10% of the institutional trading volumes).[13]

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[12]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 are already dropped due to purely engaging in market maker business), but only for those stocks for which they act as designated sponsors. The particular designated sponsors for each stock are published at www.deutsche-boerse.com.

[13]For sake of robustness, we also divided the trading day into 9 one-hour intervals but our main results do not depend on this choice, see Table 5 in the Appendix.

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Table 1: Trading Activity of Institutional Investors in the German Stock Market

Interval Number	Time Period	Average Number of Traders	Average Share of Trading Volume
1	09:00 - 09:30	25.33	6.73
2	09:30 - 10:00	21.05	5.34
3	10:00 - 10:30	15.75	2.57
4	10:30 - 11:00	22.88	6.73
5	11:00 - 11:30	19.58	4.51
6	11:30 - 12:00	18.72	4.15
7	12:00 - 12:30	17.96	3.77
8	12:30 - 01:00	17.08	3.39
9	01:00 - 01:30	17.36	4.31
10	01:30 - 02:00	16.57	3.28
11	02:00 - 02:30	17.85	3.96
12	02:30 - 03:00	18.90	4.63
13	03:00 - 03:30	18.32	4.42
14	03:30 - 04:00	20.42	6.43
15	04:00 - 04:30	20.70	6.98
16	04:30 - 05:00	20.74	7.64
17	05:00 - 05:30	22.50	10.13
18	05:30 - 08:00	18.20	10.91

Notes: This table shows the division of the trading day in 18 half-hour intervals. The opening period for the German stock exchanges at the floor is from 9 a.m. until 8 p.m. CET. On the trading platform Xetra®, on which the great majority of trades and volumes occur, trading takes place from 9 a.m. till 5.30 p.m. CET. The interval number 18 is therefore enlarged. The third column of the table reports the average of the number of traders active in each interval over the whole observation period and over all stock. The fourth column of the table reports the mean allocation of the trading volume of traders over the time intervals in percentage terms. The values are calculated as fraction of institutions trading volume in one interval according to institutions trading volume at the complete trading day and then averaged over all days and all stocks.

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. 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 defined as 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 time-series average of the coefficients is calculated: $\beta = \frac{\sum_{t=2}^{T} \beta_t}{T-1}$.

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:

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

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

where I is the number of stocks traded. D_{nit} is a dummy variable that equals one if institution n is a buyer in i at time t and zero otherwise. $D_{mi,t-1}$ is a dummy variable

that equals one if trader m (who is different from trader n) is a buyer at time $t - 1$. Therefore, the first part of the measure represents the component of the cross-sectional inter-temporal correlation that results from institutions following their own strategies when buying or selling the same stocks over adjacent time intervals. The second part indicates the portion of correlation resulting from institutions following the trades of others over adjacent time intervals. According to Sias (2004), a positive correlation that results from institutions following other institutions, i.e., the latter part of the decomposed correlation, can be regarded as evidence for herd behavior.

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 Correlated Trading by Institutions: Empirical Results

5.1 Herding measures for the whole sample period

Table 2 displays the results obtained from the Sias herding measure for institutional traders. To begin with, consider the rows presenting the herding measures calculated for the whole sample. The estimated correlation at intra-day frequency over the complete period and over all stocks is 31.12% (i.e. $\hat{\beta} = 0.3112$), which is significantly higher than the results obtained by Sias (2004) and Choi and Sias (2009) at quarterly, Puckett and Yan (2008) for weekly and Kremer and Nautz (2012) at daily frequency.[14] Decomposing the estimated coefficients into the two sources of the correlation shows that the institutional investors follow their own strategies as well as those of others. However, following Sias (2004), the average degree of *true* herding, defined as the tendency of institutions to follow the trades of others, is only 10.57%. Similar findings are obtained for the buy and sell herding measures, see panel 2 and 3 of the Table. In all cases,

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[14]The coefficients were estimated considering only intraday correlations and not the correlation between interval 18 and 1 at the next day. Including those correlation, the Sias measure slightly decreases to 28.62%. For brevity, these results are not presented, but are available on request.

the size of the adjustment in the correlation of trades confirms the importance of using investor-level data for calculating empirical herding measures.[15]

5.2 Herding in times of market turbulence

According to Hypothesis 1, herding intensity should increase in times of market turbulence, particularly during the recent financial crisis. In order to explore the empirical relevance of this simulation-based model prediction, we calculated the herding measure for the crisis and the pre-crisis period separately. The pre-crisis ends on August 9, 2007 as this is widely considered as the starting date of the financial crisis in Europe, see European Central Bank (2007).

The herding measures obtained before and during the crisis are displayed in the second and third row of Table 2. While the Sias measure is indeed significantly higher in the crisis period (10.86 > 9.50), the difference is only small and does not appear to be of economic relevance. Very similar conclusions can be drawn from the inspection of herding measures conditioned on buy and sell trades (see lower panels of Table 2) or from herding measures based on one-hour intervals, see Table 6 in the Appendix. Overall, these findings provide only weak evidence for an increased herding intensity during the crisis period.

5.3 Herding at market opening

According to Hypothesis 2, average herding intensity should be particularly low in times of a sudden inflow of new information, particularly at the opening intervals of financial markets. In order to investigate this prediction, we examine how the herding intensity changes during the course of the trading day. To that aim, we calculate the Sias herding measure for each half-hour time interval separately. The results of this exercise are presented in Table 3. The third column shows the relevant correlation resulting

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[15]Results for one-hour intervals reveal similarly a 31.26 % correlation. In that case 53% of the correlation is dedicated to institutions following themselves. The results are displayed in Table 6 in the Appendix.

Table 2: Empirical Herding Measures - Overall, Before and During the Crisis

Sample Period	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
July 2006 - March 2009	31.12 (0.01)	20.55 (0.10)	10.57 (0.11)
Pre-crisis period	33.24 (0.01)	23.74 (0.11)	9.50 (0.14)
Crisis period	29.59 (0.01)	18.73 (0.11)	10.86 (0.13)
Buy Herding			
July 2006 - March 2009	14.08 (0.23)	9.29 (0.14)	4.79 (0.11)
Pre-crisis period	14.37 (0.37)	10.27 (0.13)	4.10 (0.10)
Crisis period	13.87 (0.35)	8.78 (0.19)	5.09 (0.11)
Sell Herding			
July 2006 - March 2009	17.02 (0.14)	11.24 (0.10)	5.78 (0.10)
Pre-crisis period	18.87 (0.23)	13.46 (0.11)	5.41 (0.09)
Crisis period	15.65 (0.25)	9.91 (0.12)	5.74 (0.08)

Notes: This table reports results of the Sias measure calculated based on half-hour intervals. The correlations are displayed in percentage terms. The correlations were first estimated with a cross-sectional regression for each time interval t and stocks i. The reported correlations display the time-series average of the regression coefficients in percentage terms. The second and third column report the partitioned correlations that result from institutions following their own trades and institutions following the trades of others, see Equation (3). In the lower parts of the table the correlation is partitioned into those stocks institutions purchased in the previous time interval (buy herding) and those institutions sold (sell herding). Standard errors are given in parentheses.

Table 3: Empirical Herding Measures Throughout the Trading Day

Time Interval	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
9:30 - 10:00	25.92 (0.23)	16.00 (0.31)	9.92 (0.26)
10:00 - 10:30	28.59 (0.22)	21.05 (0.32)	7.54 (0.24)
10:30 - 11:00	30.43 (0.29)	22.58 (0.34)	7.85 (0.23)
11:00 - 11:30	34.30 (0.31)	24.32 (0.38)	9.98 (0.22)
11:30 - 12:00	33.98 (0.29)	25.74 (0.37)	8.24 (0.23)
12:00 - 12:30	33.91 (0.30)	26.08 (0.34)	7.83 (0.24)
12:30 - 01:00	33.81 (0.25)	26.85 (0.32)	6.96 (0.21)
01:00 - 01:30	33.28 (0.24)	25.44 (0.32)	7.84 (0.21)
01:30 - 02:00	34.00 (0.28)	25.44 (0.31)	8.56 (0.21)
02:00 - 02:30	34.74 (0.25)	26.14 (0.31)	8.60 (0.26)
02:30 - 03:00	33.38 (0.24)	25.09 (0.34)	8.29 (0.26)
03:00 - 03:30	34.21 (0.26)	24.90 (0.43)	9.31 (0.26)
03:30 - 04:00	34.19 (0.28)	23.59 (0.35)	10.60 (0.26)
04:00 - 04:30	35.65 (0.28)	22.79 (0.32)	12.86 (0.26)
04:30 - 05:00	34.62 (0.27)	22.72 (0.36)	11.90 (0.26)
05:00 - 05:30	32.94 (0.28)	20.41 (0.41)	12.53 (0.26)
05:30 - 08:00	18.16 (0.21)	11.80 (0.31)	6.36 (0.26)

Notes: This table reports results of the Sias measure calculated based on half-hour intervals and averaged for the specific half-hour intervals. The correlations are displayed in percentage terms. The correlations where first estimated with a cross-sectional regression for each time interval t and stocks i. The reported correlations display the time-series average of the regression coefficients in percentage terms for the respective intervals. The second and third column report the partitioned correlations that result from institutions following their own trades and institutions follow the trades of others, see Equation (3). Standard errors are given in parentheses.

Table 4: Empirical Herding Measures and the Dispersion of Analyst Recommendations

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Low Dispersion	29.39 (0.03)	15.86 (0.05)	13.53 (0.21)
Mid Dispersion	30.23 (0.02)	16.94 (0.05)	13.29 (0.24)
High Dispersion	28.49 (0.03)	16.68 (0.05)	11.81 (0.23)

Notes: This table reports results of the Sias measure calculated based on half-hour intervals and averaged for the specific dispersion tertiles. The correlations are displayed in percentage terms. See Table 2 for further information.

from institutions following other institutional trades. We find that this correlation is relatively high (9.92%) at the opening interval of the German market. Moreover, the peak of the correlation (12.86%) is found for the intervals between 3:30 and 4:30 p.m. CET (intervals 14-15), when the U.S. market opens and a lot of new information flows into the German market. Therefore, even without a formal test, there is clear evidence against Hypothesis 2. This suggests that correlated trades of institutions should not be misinterpreted as true herding. Apparently, significant herding measures point to unintentional or spurious herding, where trades of institutions are correlated because they trade upon correlated information and not because of informational cascades, see e.g. citetBS01.

5.4 Herding and disagreement among financial analysts

Let us now consider the evidence for the third hypothesis derived from the model simulation. Following Hypothesis 3, the average herding intensity should be particulary low when analysts' recommendations are more disperse. In order to investigate the empirical content of this prediction, we collect daily data from Bloomberg indicating "Buy",

"Hold" and "Sell" recommendations of financial analysts for specific stocks. Having assigned the numerical values 1, 3 and 5 accordingly, dispersion in recommendations of financial analysts is measured consistent with Brown et al. (2012) as standard deviation of all outstanding recommendations each day. Tertiles of the dispersion data is used to classify each stock at each trading day as a stock with "Low", "Mid" and "High" dispersion, respectively. In a second step, we calculate the intra-day herding measures and estimate the average for each of the three different groups separately. The results are presented in Table 4. In line with Hypothesis 3, the relevant herding measures related to "following other behavior" show that herding decreases with higher analyst dispersion. In particular, the fraction of the correlation resulting from following other traders, as displayed in column three, is lowest (11.81) for the stocks and days with high dispersions. However, the economic significance of the effect on analyst dispersion on the herding measure is merely negligible.

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. However, herd models are typically not designed to provide testable predictions about the effects of uncertainty on herding intensity. For example, in the stylized financial market of Avery and Zemsky (1998), the popular assumption that 'increased uncertainty leads to increased herding' does not hold for all parametrizations of the model. It seems that there is a lack of a direct link between herding theory and empirical work regarding the effect of various aspects of uncertainty on herding intensity. Moreover, the empirical herding literature is severely hampered by data availability. Although herd behavior in financial markets should be more of a short-term phenomenon, researchers are often forced to base their estimates either on e.g. quarterly data or on high-frequent but anonymous transaction data that does not allow to identify the trader.

With a view to these problems, the contribution of our paper is aimed to be twofold.

First, we perform numerical simulations of the herding model of Avery and Zemsky (1998) and derive three testable predictions. The simulation results show that herding intensity should be particularly high in times of market turbulence (1). Whereas herding intensity should be particularly low both, at the opening intervals of financial markets (2) and when analysts' recommendations are disperse (3). These hypotheses are investigated empirically using a novel and comprehensive high-frequent data set of the German stock market.

Our empirical results show that herding of institutional investors can hardly serve as a major explanation for the observed correlation of trades. In particular, correlated trading of institutional investors did not increase dramatically since the outbreak of the financial crisis (1). In the same vein, we found that herding intensity is only slightly lower when analysts recommendations for a certain stock are disperse (3). The results obtained for Hypothesis (2) are particularly revealing: in sharp contrast to the prediction of the herd model, we found that herding measures are significantly higher (not lower) in the opening intervals and the afternoon session when new information enters into the German stock market due to the opening of the U.S. market. This strongly suggests that the observed correlation of trades is mainly due to the common reaction of investors to new public information and should not be misinterpreted as herd behavior.

Most herding measures, including Lakonishok et al. (1992) and Sias (2004), are solely based on the correlation of trading pattern for a particular group of traders and their tendency to buy and sell the same set of stocks. In accordance with Bikhchandani and Sharma (2001), this implies that the theoretical discussion of herd behavior and the empirical specifications used to test for herding are only loosely connected. The weak support for herd behavior of institutional investors found in this paper may raise further doubts about the appropriateness of prevailing empirical herding measures. Following Cipriani and Guarino (2010), a more structural estimation of a herding model is, therefore, an interesting avenue for future research.

References

Avery, C. and Zemsky, P. (1998). Multidimensional Uncertainty and Herd Behavior in Financial Markets, *The American Economic Review* **88**(4): 724–748.

Banerjee, A. V. (1992). A Simple Model of Herd Behavior, *The Quarterly Journal of Economics* **107**(3): 797–817.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades, *Journal of Political Economy* **100**(5): pp. 992–1026.

Bikhchandani, S. and Sharma, S. (2001). Herd Behavior in Financial Markets, *IMF Staff Papers* **47**(3): pp. 279–310.

Brown, N. C., Wei, K. D. and Wermers, R. (2012). Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices, *Working paper*, University of Maryland.

Chamley, C. P. (2004). *Rational Herds*, Cambridge University Press.

Chari, V. and Kehoe, P. J. (2004). Financial crises as herds: overturning the critiques, *Journal of Economic Theory* **119**(1): 128 – 150.

Chiang, T. C. and Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets, *Journal of Banking and Finance* **34**(8): 1911 – 1921.

Choi, N. and Sias, R. W. (2009). Institutional industry herding, *Journal of Financial Economics* **94**(3): 469 – 491.

Christoffersen, S. and Tang, Y. (2009). Institutional Herding and Information Cascades: Evidence from daily trades, *Working paper*, McGill University.

Cipriani, M. and Guarino, A. (2008). Herd Behavior and Contagion in Financial Markets, *The B.E. Journal of Theoretical Economics (Contributions)* **8**(1): article no. 24.

Cipriani, M. and Guarino, A. (2010). Estimating a Structural Model of Herd Behavior in Financial Markets, *Working paper*, IMF.

Décamps, J.-P. and Lovo, S. (2006). Informational cascades with endogenous prices: The role of risk aversion, *Journal of Mathematical Economics* **42**(1): 109 – 120.

European Central Bank (2007). The implementation of monetary policy since August 2007, *Monthly Bulletin* **July**: 75–89.

Hirshleifer, D. and Hong Teoh, S. (2003). Herd Behaviour and Cascading in Capital Markets: a Review and Synthesis, *European Financial Management* **9**(1): 25–66.

Kremer, S. and Nautz, D. (2012). Short-term Herding of Institutional Traders: New Evidence from the German Stock Market, *European Financial Management* **forthcoming**.

Lakonishok, J., Shleifer, A. and Vishny, R. W. (1992). The impact of institutional trading on stock prices, *Journal of Financial Economics* **32**(1): 23 – 43.

Lee, I. H. (1998). Market Crashes and Informational Avalanches, *Review of Economic Studies* **65**(4): 741–759.

Park, A. and Sabourian, H. (2011). Herding and Contrarian Behaviour in Financial Markets, *Econometrica* **79**(4): 973–1026.

Patterson, D. M. and Sharma, V. (2010). The Incidence of Informational Cascades and the Behavior of Trade Interarrival Times during the Stock Market Bubble, *Macroeconomic Dynamics* **14**(S1): 111–136.

Puckett, A. and Yan, X. S. (2008). Short-term Institutional Herding and Its Impact on Stock Prices, *Working paper*, University of Missouri, Columbia.

Sias, R. W. (2004). Institutional Herding, *Review of Financial Studies* **17**(1): 165–206.

Vives, X. (2008). *Information and Learning in Markets*, Princeton University Press.

Wermers, R. (1999). Mutual Fund Herding and the Impact on Stock Prices, *The Journal of Finance* **54**(2): 581–622.

A   Appendix

Table 5: Intra-Day One-Hour Intervals

Interval Number	Time Period	Average Number of Traders	Average Share of Trading Volume
1	09:00 - 10:00	30.32	12.07
2	10:00 - 11:00	25.72	9.30
3	11:00 - 12:00	24.76	8.66
4	12:00 - 01:00	22.67	7.16
5	01:00 - 02:00	22.07	7.59
6	02:00 - 03:00	23.60	8.58
7	03:00 - 04:00	24.87	10.85
8	04:00 - 05:00	26.20	14.63
9	05:00 - 08:00	28.11	21.24

Notes: This table shows the division of the trading day in 9 intervals. The opening period for the German stock exchanges at the floor is from 9 a.m. until 8 p.m. CET. On the trading platform Xetra®, on which the great majority of trades and volumes occur, trading takes place from 9 a.m. till 5.30 p.m. CET. The interval number 9 is therefore enlarged. See Table 1 for further information.

Table 6: Correlations of Trades - One-Hour - Overall, Before and During the Crisis

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Whole sample	31.26 (0.12)	16.51 (0.21)	14.75 (0.21)
<08/09/07	32.97 (0.04)	18.30 (0.19)	14.67 (0.24)
≥08/09/07	30.08 (0.03)	15.27 (0.14)	14.81 (0.23)
Buy Herding			
Whole sample	14.30 (0.23)	7.55 (0.14)	6.75 (0.15)
<08/09/07	14.56 (0.37)	8.03 (0.13)	6.53 (0.15)
≥08/09/07	14.18 (0.35)	7.21 (0.19)	6.97 (0.15)
Sell Herding			
Whole sample	16.96 (0.24)	8.96 (0.20)	8.01 (0.12)
<08/09/07	18.41 (0.33)	10.27 (0.19)	8.14 (0.12)
≥08/09/07	15.90 (0.35)	8.07 (0.18)	7.83 (0.13)

Notes: This table reports results of the Sias measure calculated based on one-hour intervals. The correlations are displayed in percentage terms. See Table 2 for further information.

Table 7: Correlations of Trades - Intra-Day One-Hour Intervals

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
1-2	28.21 (0.28)	14.16 (0.21)	14.05 (0.26)
2-3	33.57 (0.32)	19.38 (0.22)	14.19 (0.24)
3-4	33.65 (0.29)	21.02 (0.24)	12.63 (0.23)
4-5	33.02 (0.31)	21.13 (0.28)	11.89 (0.22)
5-6	33.25 (0.29)	20.41 (0.27)	12.84 (0.23)
6-7	33.50 (0.30)	19.69 (0.24)	13.81 (0.24)
7-8	33.15 (0.25)	17.45 (0.22)	15.70 (0.21)
8-9	21.80 (0.25)	13.50 (0.22)	8.30 (0.21)

Notes: This table reports results of the Sias measure calculated based on one-hour intervals and averaged for the specific intervals. The correlations are displayed in percentage terms. The correlations were first estimated with a cross-sectional regression for each time interval t and stocks i. See Table 3 for further information.

Table 8: Correlations of Trades - One-Hour - Dispersion of Opinions

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Low Dispersion	29.85 (0.03)	13.14 (0.21)	16.71 (0.21)
Mid Dispersion	30.94 (0.04)	14.28 (0.19)	16.66 (0.24)
High Dispersion	29.40 (0.03)	14.93 (0.14)	14.47 (0.23)

Notes: This table reports results of the Sias measure calculated based on one-hour intervals and averaged for the specific dispersion tertiles. The correlations are displayed in percentage terms. See Table 2 for further information.