Can Correlated Trades in the Stock Market be Explained by Informational Cascades? Empirical Results from an Intra-Day Analysis

Stephanie Kremer
Freie Universität Berlin

Dieter Nautz*
Freie Universität Berlin

May 13, 2011

Abstract

In highly developed financial markets, herd behavior driven by informational cascades should be mainly an intra-day phenomenon. This paper employs a comprehensive database of all real-time transactions made by financial institutions in the German stock market in order to investigate to what extent and under what circumstances institutions follow other institutions within a trading day. Models of informational cascades predict that herd behavior and the correlation of trades should be more pronounced in times of uncertainty. Our empirical results show that the observed correlation of trades cannot be explained by informational cascades. In particular, we find only weak evidence for higher herding measures in the crisis period. Moreover, the correlation among trades is found to be particularly strong in times of low analyst dispersion and at market openings when a lot of new information flows into the market.

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

JEL classification: G11, G24, C23

---

*Department of Economics, Boltzmannstraße 20, D-14195 Berlin, Germany. E-Mail: stephanie.kremer@fu-berlin.de, dieter.nautz@fu-berlin.de. Support by the Deutsche Forschungsgemeinschaft (DFG) through the CRC 649 "Economic Risk" is gratefully acknowledged. Thanks to Matthias Weiß for helpful research assistance.

1 Introduction

Increasing empirical literature provides evidence on "correlated trading" of institutional investors, see, e.g., Sias (2004). However, the rational behind this trading behavior and its consequences for the functioning of financial markets are still unclear. On the one hand, correlated trading can occur as investors react commonly on the same public information.On the other hand, correlated trading might be a result of informational cascades, where investors ignore their own noisy information and imitate other market participants, since they infer (from observed trading behavior) that others have relevant information, see Bikhchandani et al. (1992) and Avery and Zemsky (1998). As a result, correlated trading driven by informational cascades should be particularly pronounced in times of uncertainty. This paper uses a comprehensive data set to test this theoretical prediction.

Informational cascades occur in the short-term and are more of an intra-day phenomenon, especially in developed markets. The arrival of public information and consequent price adjustments will dominate information from observed behavior and stop incorrect cascades, see Christoffersen and Tang (2009) and Patterson and Sharma (2010). Hence, the empirical assessment of cascades 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 previous literature, using the measures developed by Lakonishok, Shleifer and Vishny (1992) or Sias (2004), focusses on institutions' changes in quarterly holdings which cannot account for the short-term character of informational cascades. Recently, Patterson and Sharma (2010) analyze cascades in the U.S. market in the 1998-2001 period within an intra-day context.[1] Their proposed method is based on counting runs of buy or sell trades. The intuition is that longer sequences of buy and sell trades are evidence for informational cascades. They consider trade data that do not differentiate at investor level. Hence, it is not possible to differentiate between traders that indeed follow predecessors and

[1]Lin, Tsai and Sun (2009) apply the same methodology analyzing the Taiwan stock market.

traders that simply follow themselves, because they split their trades; a differentiation accounted for by Sias (2004).

This paper contributes to the literature by analyzing higher frequent 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 carried out by banks and financial services institutions trading for their own account on German stock exchanges. We analyze the transactions of financial institutions in stocks included in the major German stock index DAX 30 over the period from July 2006 to March 2009. To test for the formations of informational cascades we use the method developed by Sias (2004), testing for positive correlations of the fraction of institutions buying in time intervals within a day. The method allows for the division of the correlation into its components, i.e. whether the institutions follow their own trades or whether the correlation in fact results from institutions follow other institutions into and out of the same stocks. Since our data allow for the direct identification of the trader, we are, to our knowledge, the first applying this measure in the intra-day context.

Our estimation results reveal that transactions of financial institutions are actually correlated within a trading day. When decomposing the correlation, we find that the correlation stems from both sources: Institutions following own trades as well as following other institutions. Hence, our findings support the use of investor-level data to account for sequential trades by single institutions.

According to the informational cascade models of Bikhchandani et al. (1992), Banerjee (1992), and Avery and Zemsky (1998), an important precondition for cascades in the stock market with flexible prices is uncertainty about the value of an asset and the accuracy of information. In order to analyze whether the "following other institutions" behavior indeed can be regarded as formation of informational cascades, we test three theoretical predictions centering around this prediction: First, cascades should be observed in times of market stress, as associated with higher uncertainty. However, our results show only weak evidence for higher correlations in the market turbulence during the crisis. Second, cascades should be observed in times with fewer information in the market. Yet, our estimation results reveal that correlation of trades is 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, cascades will be observed in times with higher analyst dispersion as a measure of uncertainty about the asset value. However, we rather find a negative relationship between the Sias measure and analyst dispersions. Overall, our evidence does not support the theory of informational cascades. Our results are more in line with Lin, Tsai and Sun (2009) suggesting correlated trading activity rather resulting unintentionally, probably through the common reaction on information.

The rest of the paper is structured as follows: Section 2 reviews the theory on informational cascades. Section 3 and 4 introduce the data and discuss the Sias herding measure. Section 5 presents the empirical results on the testable hypotheses. Section 6 contains a summary of the main results and offers some concluding remarks.

2 The Theory of Informational Cascades

2.1 Informational Cascade Models

Informational cascades occur as a sequence of decisions where rational investors disregard their own information and preferences in favor of following the decisions of investors ahead. Hence, investors rationally copy actions despite having different information. According to the information cascade model of Bikhchandani, Hirshleifer and Welch (1992), a group of investors decide in sequence whether to adopt or reject a possible action; i.e. whether to invest in the stock or not. The decision makers have two sources of information: Each investor observes the trade decisions of all investors ahead. Additionally, each investor has information regarding the value of the asset, but this information is incomplete and noisy. However, the two sources of information may present conflicting signals. All investors follow Bayesian rationality. If the decision maker's own information is limited, he may put more weight on the information derived from the observation of others' actions. Hence, investors may ignore their own signal and follow the behavior of the preceding deciders only, resulting in an informational cascade. The underlying message of the informational cascades theory is that the influence of others' actions can be substantial that it dominates the the own information, as this own information is uncertain. Hence, uncertainty in the decision makers own information is the key factor driving informational cascades.

The model of Avery and Zemsky (1998) extend the assumption of Bikhchandani et al.'s (1992) model by introducing a market maker adjusting prices. The flexible prices reduce the likeliness of cascades compared to the original model. The market maker incorporates all publicly available information in the prices. In this setting it is optimal to trade based on own information than upon observed behavior of predecessors. However, if the market maker has information disadvantages, prices are not adjusted effectively. Thus, according to Avery and Zemsky (1998) cascades occur more infrequently and require additional uncertainty compared to the model of only Bikhchandani et al. (1992). Conditions for the cascades in this setting are the uncertainty about the value of the stock, the uncertainty about the accuracy of information and information asymmetry.

The empirical approaches examining cascade behavior can be divided into analyzes of market data and laboratory experiments. Laboratory experiments have the advantage that they directly allow to control for public and private information. Hence theoretical predictions are explicitly testable, see, e.g., Alevy, Haigh and List (2007). Early laboratory experiments indeed detect informational cascading behavior, see, e.g., Anderson and Holt (1997) as first application. However, more recent evidence form experiments questions a distinct imitative behavior. Alevy et al. (2007) experimented explicitly with market professionals. They find that market professionals tend to make use of their private signal to a greater degree and base their decisions on the quality of the public signal to a greater extent, than do students with which experiments usually are conducted. Also, results of Weizscker (2010) indicate that people assign much more weight on their own information relative to the publicly observable decisions. Additionally, Drehmann, Oechssler and Roider (2005) do not find evidence for imitative behavior in their financial market experiment. In contrast, participants rather show contrarian behavior against the market trend as they mistrust the decisions of others.

Analysis on market data have, in contrast to laboratory experiments, the disadvantage that the motives behind a financial decision are not directly discernable. A large number of factors may influence an investment decision and controlling for underlying fundamentals is difficult. Hence, empirically, a direct link between theoretical predictions and behavior is problematic, see Alevy et al. (2007) and Bikhchandani and Sharma (2001).

2.2 Testable Hypotheses

To capture this link within our analysis to the extent possible, we follow e.g. Patterson and Sharma (2010) and make use of the theoretical implications. Overall, the above summarized models in general imply cascades to be observed in cases of lower information quantity and precision and higher information uncertainty and asymmetry. Hence, the theory of informational cascades leads to the following testable predictions:

H1: Informational cascades will be observed in times of market turbulence. This prediction derives from the assumption that times of market stress are associated with increased uncertainty and investor anxiety, see Patterson and Sharma (2010). We will test the hypothesis by estimating correlations separately for the crisis and non-crisis period.

H2: Informational cascades will be observed in times with fewer public information in the market. This prediction directly indicates the theoretical relation between informational cascades and lower information quantity, see Lin, Tsai and Sun (2009). The hypothesis is tested by accounting for time intervals during the day in which information flows into the market.

H3: Informational cascades will be observed in times where analysts opinions disperse. This prediction derives from the assumption that dispersions of analyst options capture the magnitude of beliefs heterogeneity. Higher dispersions indicate higher information uncertainty and asymmetry, see Brown, Wei and Wermers (2010) and Christoffersen and Tang (2009). We will test the hypothesis by classifying the standard deviation of analyst recommendations in tertiles and estimating correlations accordingly.

3 Data and Sample

The paper employs 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.[2]

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 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.[3]

[2] Kremer and Nautz (2010) use the data as first and show the impact of data-frequency on herding levels by comparing quarterly, monthly and daily calculations. 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.

[3] 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.

Table 1: Intra-Day Half-Hour Intervals

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.

The study covers data from July 2006 until March 2009 (a total of 698 trading days).[4] Over this observation period 1,044 institutions traded in DAX 30 stocks on German stock exchanges. For our analysis, we divide each trading day into 18 half-hour intervals as displayed in Table 1. The third and fourth column of Table 1 show the average trading activity during one trading day. The number of institutions trading is relatively stable over the different intervals, while most traders are active at the opening (about 25) and closing interval. Nevertheless, in each interval, enough institutions are active to perform the intra-day analysis. The fourth column of Table 1 provides for information regarding the dispersion of the volumes of trades of the institutions in percentage terms over the trading day. Again, the highest amounts are on average traded at the beginning (about 7%) and at the end of the day (about 10% of the institutional trading volumes at the day).

For robustness tests, we also divide the trading day into 9 one-hour intervals, see Table 5 in the Appendix. Our results are displayed in the Appendix and will not change qualitatively due to this one-hour based division.

4 The Methodology

The dynamic herding measure proposed by Sias (2004) explores whether investors follow each others' trades by examining the correlation between the traders buyers tendency over time. The starting point of the Sias measure is the number of buyers as a fraction of all traders. 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

[4] The stocks were selected according to the index compositions at the end of the observation period on March 31, 2009.

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 N_{it} is the number of institutions trading stock i at time t and 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 first evidence for informational cascades.

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 Correlations of Trades

The methodology of Sias (2004) explores whether the buying tendency of traders persists over time. The motivation for adopting this approach is to identify informational cascades. To this end, the Sias measure directly indicates whether institutional investors follow each others' trades by examining the correlation between institutional trades in one time interval and the next interval. In contrast to approaches using anonymous transaction data, see, e.g. Patterson and Sharma (2010), applying this measure to investor-level data directly enables us to explore the extent to which traders follow indeed others and not themselves.

Table 2 displays the results obtained from the Sias herding measure for institutional traders. Consider first only the rows for the "whole sample". The estimated correlation at intra-day frequency over the complete period and over all stocks in the datasample is 31.12% (coefficient $\beta = 0.3112$), 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 (2010) at daily frequency.[5]

After the decomposition of the coefficient into the two different sources of the correlation, results reveal that the institutions follow their own strategies as well as those of others (i.e., herd) into and out of stocks. The higher part of the correlation, about 66% (=0.2055/0.3126), results from institutions that follow their own trading strategies. Hence, this result supports methods taking into account investor-level data and indicates that correlations on anonymous data must be interpreted with caution. The role of split trades of single institutions becomes even more relevant in case of higher frequency data. With the length of the period under investigation, the part of the correlation dedicated to "follow on trades" behavior shrinks.[6]

[5] 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.

[6] Results for one-hour intervals reveal similarly a 31.26 % correlation. In that case 53% of the

Table 2: Correlations of Trades - Overall, Before and During the Crisis

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
Whole sample	31.12 (0.01)	20.55 (0.10)	10.57 (0.11)
<08/09/07	33.24 (0.01)	23.74 (0.11)	9.50 (0.14)
≥08/09/07	29.59 (0.01)	18.73 (0.11)	10.86 (0.13)
Buy Herding			
Whole sample	14.08 (0.23)	9.29 (0.14)	4.79 (0.11)
<08/09/07	14.37 (0.37)	10.27 (0.13)	4.10 (0.10)
≥08/09/07	13.87 (0.35)	8.78 (0.19)	5.09 (0.11)
Sell Herding			
Whole sample	17.02 (0.14)	11.24 (0.10)	5.78 (0.10)
<08/09/07	18.87 (0.23)	13.46 (0.11)	5.41 (0.09)
≥08/09/07	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.

Nevertheless, results displayed in column 3 of Table 2 reveal a correlation of 10.57% for institutions following the trades of others. This finding may suggest the building up of informational cascades during a trading day. However, the correlation may also stem from institutions trading sequentially on correlated information.

5.2 The Role of the Crisis

H1: Informational cascades will be observed in times of market turbulence.

According to the models of Bikhchandani et al. (1992) and Avery and Zemsky (1998), informational cascades occur in times of market turbulence as those are associated with increased uncertainly and investor anxiety, see Patterson and Sharma (2010) and Choi and Sias (2009). The main intuition is that if agents have a weak information signal and a lot of uncertainty about the value of an asset but observe a lot of trading in the asset, they are more likely to ignore their own signals and follow the crowd. To examine this issue, we divide our sample into crisis and non-crisis periods, i.e., before and after August 9, 2007 as this date is widely considered as starting point of the financial crisis.

However, results displayed in the second and third row of Table 2 reveal only weak evidence for higher "following others" behavior during the crisis period, contradicting the implications of the information cascade model.[7] Also, differentiating between correlations resulting from buy and sell trades does not show notifiable differences. However, overall there seems to be a slightly higher herding tendency on the sell side.

5.3 The Availability of Information

H2: Informational cascades will be observed in times with fewer public information in the market.

---

correlation is dedicated to institutions following themselves. The results are displayed in Table 6 in the Appendix. Kremer and Nautz (2010) show lower proportions considering monthly and quarterly data.

[7] Results for one-hour intervals will not change this conclusions and are are displayed in Table 6 in the Appendix.

Table 3: Correlations of Trades - Intra-Day Half-Hour Intervals

	Average Correlation	Partitioned Correlation	
		Follow Own Trades	Follow Trades of Others
1-2	25.92	16.00	9.92
	(0.23)	(0.31)	(0.26)
2-3	28.59	21.05	7.54
	(0.22)	(0.32)	(0.24)
3-4	30.43	22.58	7.85
	(0.29)	(0.34)	(0.23)
4-5	34.30	24.32	9.98
	(0.31)	(0.38)	(0.22)
5-6	33.98	25.74	8.24
	(0.29)	(0.37)	(0.23)
6-7	33.91	26.08	7.83
	(0.30)	(0.34)	(0.24)
7-8	33.81	26.85	6.96
	(0.25)	(0.32)	(0.21)
8-9	33.28	25.44	7.84
	(0.24)	(0.32)	(0.21)
9-10	34.00	25.44	8.56
	(0.28)	(0.31)	(0.21)
10-11	34.74	26.14	8.60
	(0.25)	(0.31)	(0.26)
11-12	33.38	25.09	8.29
	(0.24)	(0.34)	(0.26)
12-13	34.21	24.90	9.31
	(0.26)	(0.43)	(0.26)
13-14	34.19	23.59	10.60
	(0.28)	(0.35)	(0.26)
14-15	35.65	22.79	12.86
	(0.28)	(0.32)	(0.26)
15-16	34.62	22.72	11.90
	(0.27)	(0.36)	(0.26)
16-17	32.94	20.41	12.53
	(0.28)	(0.41)	(0.26)
17-18	18.16	11.80	6.36
	(0.21)	(0.31)	(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 3 breaks down the correlations into the intra-day intervals. The third column again shows the correlation resulting from institutions following other institutional trades. Those correlations are higher at the beginning of the trading day, suggesting that intra-day herding occurs very likely in the opening interval with a correlation of 9.92%. This finding is in line with the evidence provided by Lin et al. (2009) and rather implies unintentional herding which is based on publicly available information. Opening intervals are those with highest information in the market. The model of Back, Cao and Willard (2000) suggests that at the market opening informed investors trade heavy with correlated information. Lin et al. (2009) argue therefore that herding at market opening should not be explained by information cascades.[8]

However, as market goes further to near close, an information cascade effect might increase. Actually, around the mid-day, correlations are lowest but then rise slightly. The peak of the correlation, i.e. 12.86%, is found for the intervals between 3:30 and 4:30 p.m. CET (intervals 14-15). While Lin et al. (2009) suggest informational cascades are most likely in the close interval, for the German stock market we have to consider a different interpretation: In fact, the U.S. market opens at 3:30 p.m. CET, introducing new information into the German market. Hence, higher correlations in these time zones are again consistent with institutions trading on correlated information and thus again result less likely from informational cascades.

5.4 The Dispersion of Opinions

H3: Informational cascades will be observed in times where analysts opinions disperse.

The theory of Avery and Zemsky (1999) predicts that informational cascades occur under the conditions of information asymmetry and uncertainty. Shares included in the DAX 30 are those with highest market capitalization, trading volumes and transparency among the German stock market. Hence, those stocks are attributed with less

[8] They rather relate their finding to the search model of Vaxanos and Wang (2007) and argue that stronger herding is driven by shorter search time and lower transaction costs. Trading concentration occurs where investors with similar costs choose to trade similar assets.

Table 4: Correlations of Trades - Dispersion of Opinions

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

information asymmetry and uncertainty. Hence, correlated trading evidence in DAX 30 stocks may rather result from correlated information than from the formation of informational cascades.

To further investigate whether the evidence of correlated trading activity during the day in DAX 30 stocks results from informational cascades, we investigate the impact of dispersion of opinions among investors on herding. Analyst dispersion captures the magnitude of beliefs heterogeneity and is a measure of information uncertainty and asymmetry, see Christoffersen and Tang (2009). If the correlation of institutional trades stems from informational cascades, we would expect higher levels of beliefs' dispersion arising from noisy information leading to higher "following others" behavior. The models of informational cascades would then imply that investors are more likely to herd as they infer information from others.

Dispersion in opinions is measured consistent with Brown et al. (2010) as standard deviation of all outstanding recommendations each day. Analyst recommendations received from Bloomberg indicate "Buy", "Hold" and "Sell" and are assigned to the numerical values 1, 3 and 5. The dispersion variable shows how information is correlated across informed agents. While a low dispersion indicates a general agreement and thus correlated information in the market, a high dispersion indicates noisy information and thus information uncertainty, a condition under which informational cascades build up.

We classify different stocks i at different trading days into three groups on the basis of the standard deviation, i.e. "Low", "Mid" and "High" dispersion. We then investigate intra-day correlations and estimate averages separately for the three different groups. Results are presented in Table 4 and reveal that the "following other behavior" is not attributed to higher dispersions in opinions. In fact, the fraction of the correlation resulting from following other traders, as displayed in column three, is lowest for the stocks and days with "Highest" dispersions. Hence, the higher the level of dispersion of opinion among investors the less are trades correlated. The hypothesis is rejected and, therefore, the evidence does not support the models of informational cascades.

6 Conclusion

This paper contributes to the existing literature on informational cascades using high-frequent investor-level data that directly identify transactions by each trader. To investigate the formations of informational cascades, we apply the method developed by Sias (2004) to intra-day data. In line with earlier evidence on antonymous transaction data, our results reveal strong correlation of institutional transactions during a day. However, our investor- specific data show that the correlation stems from both sources: Institutions following other institutions and institutions following own trades, as they may split their transactions. The following own trades part becomes even more pronounced using higher frequency data. Hence, our findings emphasize the use of investor-level data to account for institutions that build on sequential own trades.

An important precondition for informational cascades in the stock market is uncertainty above the value of an asset and regarding the accuracy of information. Deriving from these implications, we test three hypotheses. Yet, our results cannot confirm higher "following others" behavior in times of market turbulence during the crisis. Moreover, we find rather a negative relationship between the Sias measure and analyst dispersions which capture uncertainty regarding the asset values. Furthermore, our estimation results reveal that correlation of trades is 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. Overall, our results do not support the popular theory of informational cascades as explanation for correlated trading. Our findings rather suggest that correlated trading activity results unintentionally, through the common reaction on information.

On the one hand, our findings are in line with recent evidence from laboratory experiments, also questioning imitative behavior in the financial market, see, e.g., Drehmann et al. (2005). On the other hand, one could argue that the evidence is based on a statistical method only measuring correlations and not on a full-fledged model for trading behavior. A first step in the direction to a structural estimation framework has been recently suggested by Cipriani and Guarino (2010), as interesting avenue for future research.

References

Alevy, J. E., Haigh, M. S. and List, J. A. (2007). Information Cascades: Evidence from a Field Experiment with Financial Market Professionals, *Journal of Finance* **62**(1): 151–180.

Anderson, L. R. and Holt, C. A. (1997). Information Cascades in the Laboratory, *American Economic Review* **87**(5): 847–862.

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

Back, K., Cao, H. and Willard, G. (2000). Imperfect Competition among Informed Traders, *Jounal of Finance* **55**(5): 2117–2155.

Banerjee, A. (1992). A Simple Model of Herd Behavior, *Quarterly Journal of Economics* **107**: 797–818.

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**: 992–1026.

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

Brown, N., Wei, K. and Wermers, R. (2010). Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices, *Working Paper, University of Maryland* .

Choi, N. and Sias, R. W. (2009). Institutional Industry Herding, *Journal of Financial Economics* **94**: 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. (2010). Estimating a Structural Model of Herd Behavior in Financial Markets, *IMF Working Paper* .

Kremer, S. and Nautz, D. (2010). Short–Term Herding of Institutional Traders: New Evidence from the German Stock Market, *European Financial Management* **forthcoming**.

Lakonishok, J., Shleifer, A. and Vishny, R. (1992). The Impact of Institutional Trading on Stock Prices, *Journal of Financial Economics* **32**: 23–43.

Lin, W., Tsai, S.-C. and Sun, D. (2009). What Causes Herding: Information Cascade or Search Cost?, *MPRA Working Paper* **21204**.

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

Vaxanos, D. and Wang, T. (2007). Search and Endogenous Concentration of Liquidity in Asset Markets, *Journal of Economic Theory* **136**: 66–104.

Weizscker, G. (2010). Do We Follow Others When We Should? A Simple Test of Rational Expectations, *American Economic Review* **100**: 2340–2360.

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	14.16	14.05
	(0.28)	(0.21)	(0.26)
2-3	33.57	19.38	14.19
	(0.32)	(0.22)	(0.24)
3-4	33.65	21.02	12.63
	(0.29)	(0.24)	(0.23)
4-5	33.02	21.13	11.89
	(0.31)	(0.28)	(0.22)
5-6	33.25	20.41	12.84
	(0.29)	(0.27)	(0.23)
6-7	33.50	19.69	13.81
	(0.30)	(0.24)	(0.24)
7-8	33.15	17.45	15.70
	(0.25)	(0.22)	(0.21)
8-9	21.80	13.50	8.30
	(0.25)	(0.22)	(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	13.14	16.71
	(0.03)	(0.21)	(0.21)
Mid Dispersion	30.94	14.28	16.66
	(0.04)	(0.19)	(0.24)
High Dispersion	29.40	14.93	14.47
	(0.03)	(0.14)	(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.