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Full Length Article

Information cascades, short-selling constraints, and herding in equity markets☆

Murat Tiniç [a,*], Muhammad Sabeeh Iqbal [b], Syed F. Mahmud [c]

[a] *Kadir Has University, Faculty of Management, 34083 Istanbul, Turkey*
[b] *Bilkent University, Faculty of Business Administration, 06800 Bilkent Ankara, Turkey*
[c] *Social Sciences University of Ankara, Department of Economics, 06050 Ulus Ankara, Turkey*

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Abstract

This paper examines the relationship between informed trading and herding in Borsa İstanbul. Our firm-level cross-sectional analysis asserts that informed trading can significantly increase future herding levels. Furthermore, we show that the relationship between informed trading and herding intensifies under short-selling restrictions. Our results confirm the predictions of the informational cascades framework where the individuals disregard their private information to follow others. We show that information cascades are relevant both for buy-side herding and sell-side herding. Short-selling restrictions may reinforce the herding behaviour since informed investors may not be able to clear out potential price misalignments.

JEL classification: G11; G12; G14

Keywords: Informed trading; Herding; Informational cascades; Short-selling restrictions

1. Introduction

Herding is defined as the persistence in the order flow generated due to the potential tendency of investors to make decisions with respect to collective actions of the market, rather than their own beliefs. Market participants may tend to follow each other in their investment behavior. Herd behavior in buying and selling the same stock could be due to behavioral reasons such as reputational concerns of the money managers (Scharfstein & Stein, 1990) or the preference of certain stock characteristics by investors (Falkenstein, 1996). On the other hand, herding can also be observed as correlated private information about the stock's fundamentals (Froot et al., 1992) or tendency to follow a better-informed counterpart (Bikhchandani et al., 1992). The latter is referred to as informational reasons to herd, or information driven herding. In the behavioral herding model of Scharfstein and Stein (1990), money managers herd since they consider moving against the crowd detrimental for their reputation. They explain it via "sharing the blame effect" in the case of a systematic unpredictable shock. Falkenstein (1996) shows, on the other hand, inclinations of investors towards certain stock characteristics such as liquidity or past performance can give rise to imitating behavior among investors. Information asymmetry can also be an important stock characteristic that drive the herd behavior. Overall, information asymmetry in trading a certain asset can lead imitating behavior among investors due to the risks associated to trading with an informed counterpart. In this paper, we primarily examine the relationship between informed trading and herding in Borsa İstanbul

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* Corresponding author.
E-mail address: murat.tinic@khas.edu.tr (M. Tiniç).
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(BIST). We further assess the impact of short-selling restrictions on this relationship.

Our paper is, therefore, motivated by the academic debate about the relationship between information asymmetry and herding. On one hand, in the informational cascade model of Bikhchandani et al. (1992), individuals disregard their private information and follow those who they think are more informed. Wermers (1999) argues that uninformed investors are expected to follow informed investors when there is high information asymmetry in the market. Informational cascades model inherently assumes that uninformed investors only observe the past actions of informed investors, but they are not able to observe private signals about the fundamental value of the asset. This implies that uninformed investors can only invest based on mimicking strategies of informed traders rather than their beliefs. To that end, the information cascades Hypothesis predicts a positive relationship between informed trading activity and future herding levels. On the other hand, investigative herding arises when a crowd of investors interprets the existing information similarly. This causes a convergence in the investment strategies as they drive similar conclusions from their analysis. Sias (2004) argues that investigative herding is evident in a market with low information asymmetry and therefore it postulates negative relationship between informed trading activity and future herding levels.

A number of studies have examined herd behavior in Borsa Istanbul (BIST). Balcilar and Demirer (2015) show that the aggregate herding behavior in the Turkish equities is dependent upon global shocks and volatility. Demir et al. (2014, pp. 389−400) show that market-level sentimental herding significantly increases during times of high local uncertainty (2000−2001 Turkish banking crisis). Furthermore, Solakoglu and Demir (2014) argue that small investors generate sentimental herding in BIST. They find no evidence of sentimental herding in large-cap stocks More recently, Dalgıç et al. (2019) examine the daily and intraday herding behavior of different investor groups in BIST. They show that non-professional investors in BIST tend to act more collectively in their investments compared to professional investors. There is also a growing interest in the role of information asymmetry on the stocks trades in BIST. Tiniç and Savaşer (2020) examine the informational differences between foreign and domestic investors in BIST. They indicate that foreigners have a limited price impact over the Turkish stocks, which implies that foreign investors have an informational disadvantage in the Turkish market. Tiniç and Salih (2020) show that information asymmetry is an idiosyncratic risk in BIST which can be eliminated with portfolio diversification.

To conduct our analysis, we rely on the sequential trading model of Easley et al. (1996) and estimate the probability of informed trading adjusted for symmetric order flow shocks (Duarte & Young, 2009). We also use one of the most widely used herding measure proposed by Lakonishok et al. (1992) to proxy herding. Using the intraday trade-book data for all stocks listed on BIST between January 2005 and April 2017, we test the baseline Hypothesis that information asymmetry has no impact on herding through firm-level cross-sectional regressions (Fama & MacBeth, 1973). Based on our analysis, we reject the null hypothesis and conclude that informed trading can significantly predict the herd behavior even after we control for firm-specific characteristics such as size, profitability, risk (both systematic and idiosyncratic), liquidity and past return performance. For our full sample analysis, we observe that a one percent increase in the informed trading levels increases the future herding levels by 50 bps, on average. The positive relationship between information asymmetry levels and future herding levels support the predictions of the information cascades hypothesis.[1]

Turkish market also provides a natural experiment to examine the impact of short-selling restrictions on the relationship between information asymmetry and herding. Capital market regulators have put temporary restrictions on short-selling in BIST between August 2011 and July 2012. Our results show that average herding levels increase significantly, under short-selling restrictions. In addition, informational cascades Hypothesis on the buy-side herding is most evident during the times of short-selling restrictions since informed traders could not be able to clear away potential price misalignments (Alkan & Guner, 2018).

Overall our results are consistent with the previous findings document by Zhou and Lai (2009) and Alhaj-Yaseen and Rao (2019) which argue that informational cascades can be the driving factor of herding in the equity markets. In addition, we show that short-selling restrictions amplify the informational cascades in equity markets.

Our research contributes to the growing literature that examines the determinants of herding behavior in equity markets. Even though there are well-established theoretical foundations, the number of empirical studies on the relationship between information asymmetry and herding is quite small. To the best of our knowledge, this paper is first to examine the impact of short-selling restrictions on the relationship between herding and information asymmetry.

Our paper is organized as follows; Section 2 presents the herding measure and the probability of informed trading measure. Section 3 describes the data. Section 4 discusses the methodology. Section 5 presents the results. Section 6 concludes.

2. Herding and PIN measures

2.1. Herding

We rely on the proxy proposed by the seminal work of Lakonishok et al. (1992) to measure herding. For given stock i on month t, we calculate the level of herding as follows;

[1] Furthermore, we repeat the analysis for buy-side and sell-side herding measures and find that the predictive relationship between information asymmetry and future herding levels are evident for both buy-side and sell-side herding.

$$H_{it} = \left|\frac{B_{it}}{N_{it}} - E\left(\frac{B_{it}}{N_{it}}\right)\right| - E\left|\frac{B_{it}}{N_{it}} - E\left(\frac{B_{it}}{N_{it}}\right)\right| \tag{1}$$

where B_{it} is the number of buy trades for stock i in month t. N_{it} is the total number of trades defines as the sum of total buy and sell trades for stock i in month t. If there is herding on the buy-side of the market then we expect a high proportion of buy orders on that stock relative to the cross-sectional average, $E\left(\frac{B_{it}}{N_{it}}\right)$, which is given by;

$$E\left(\frac{B_{it}}{N_{it}}\right) = \frac{1}{I}\sum_{i=1}^{I}\frac{B_{it}}{N_{it}} \tag{2}$$

where I is the total number of stocks. $E\left|\frac{B_{it}}{N_{it}} - E\left(\frac{B_{it}}{N_{it}}\right)\right|$ represents an adjustment factor. This adjustment is required since AF is different than zero in case of no herding. To compute the adjustment factor, we assume that B_{it} follows a binomial distribution. Given this assumption, each order is a trial with a probability of success (that is, the probability of being a buy order) equal to the cross-sectional average. We obtain the expected absolute variation of buy proportion around the cross-sectional mean for each stock quarter as below;

$$E\left[\frac{B_{it}}{N_{it}} - E\left(\frac{B_{it}}{N_{it}}\right)\right] = \sum_{b=0}^{N_{it}} p_b\left(\frac{b}{N_{it}} - \frac{1}{I}\sum_{i=1}^{I}\frac{B_{it}}{N_{it}}\right) \tag{3}$$

where b corresponds to the number of buy orders which takes values from 0 to N_{it} and p_b is the binomial probability calculated as follows;

$$p_b = \binom{N_{it}}{b}\rho^b(1-\rho)^{(N_{it}-b)} \tag{4}$$

for $b \in \{0, \ldots, N_{it}\}$ where ρ is the probability of success. Hence p_0 is the probability that there are zero buys for stock i.

We closely follow Wermers (1999) and Yuksel (2015) to distinguish between buy and sell herding. We set our buy (sell) herding variable BH_{it} (SH_{it}) as follows;

$$BH_{it} = \frac{H_{it}}{\frac{B_{it}}{N_{it}}} > E\left(\frac{B_{it}}{N_{it}}\right) \quad SH_{it} = \frac{H_{it}}{\frac{B_{it}}{N_{it}}} < E\left(\frac{B_{it}}{N_{it}}\right) \tag{5}$$

In line with Yuksel (2015), we make the final adjustment by subtracting $\min(BH_{it})$ from BH_{it} and $\min(SH_{it})$ from SH_{it}.

2.2. Probability of informed trading

To measure information asymmetry for each stock, we rely on the sequential trading model of Easley et al. (1996) which assumes that on a given trading day t, an information event occurs with probability α. This information event is assumed to generate a bad (good) signal for the underlying value of the equity with probability $\delta(1-\delta)$. Informed investors are assumed to arrive at the market following a Poisson process with a parameter μ to buy (sell) only when there is good (bad) news; that is, they are assumed to interpret the information event and the corresponding signal, perfectly. Uninformed investors arrive at the market independent from the information event or its content. They follow a Poisson process with parameter $\varepsilon_b(\varepsilon_s)$ to place buy (sell) orders.

Then for a given trading day t, the joint probability distribution for observing buy and sell orders (B_t, S_t) given the parameter vector $\Theta = \{\alpha, \delta, \mu, \varepsilon_b, \varepsilon_s\}$ can be written as follows;

$$\begin{aligned} f(B_t, S_t|\Theta) = {} & \alpha\delta\exp(-\varepsilon_b)\frac{(\varepsilon_b)^{B_t}}{B_t!}\exp(-\varepsilon_s+\mu)\frac{(\varepsilon_s+\mu)^{S_t}}{S_t!} \\ & +\alpha(1-\delta)\exp(-\varepsilon_b+\mu)\frac{(\varepsilon_b+\mu)^{B_t}}{B_t!}\exp(-\varepsilon_s)\frac{(\varepsilon_s)^{S_t}}{S_t!} \\ & +(1-\alpha)\exp(-\varepsilon_b)\frac{(\varepsilon_b)^{B_t}}{B_t!}\exp(-\varepsilon_s)\frac{(\varepsilon_s)^{S_t}}{S_t!} \end{aligned} \tag{6}$$

The parameter estimates $\widehat{\Theta} = \{\widehat{\alpha}, \widehat{\delta}, \widehat{\mu}, \widehat{\varepsilon_b}, \widehat{\varepsilon_s}\}$ are obtained by the joint log-likelihood function given the order input matrix (B_t, S_t) over T trading days. The objective function of this problem is given by;

$$L(\Theta|T) \equiv \sum_{t=1}^{T} L(\Theta|(B_t, S_t)) = \sum_{t=1}^{T}\log(f(B_t, S_t, |\Theta)) \tag{7}$$

The maximization problem is subject to boundary constraints $\alpha, \delta \in [0, 1]$ and $\mu, \varepsilon_b, \varepsilon_s \in [0, \infty)$. The PIN estimate is then given as the proportion of informed investors in the market;

$$\widehat{PIN} = \frac{\widehat{\alpha}\widehat{\mu}}{\widehat{\alpha}\widehat{\mu} + \widehat{\varepsilon_b} + \widehat{\varepsilon_s}} \tag{8}$$

We use a modified version of PIN where the measure is adjusted for symmetric order flow shocks. A detailed explanation of our estimation procedure is provided in Appendix.

3. Data

Borsa İstanbul is a fully electronic order-driven market where the main trading system is a continuous auction through a limit order book. Trading in the equity market is conducted through price and time priority.

Our dataset consists of intraday trades of all stocks traded in BIST, from March 2005 to April 2017. During our sample period, 498 different stocks are traded in BIST. We obtain price and accounting information from Bloomberg Terminal and calculate the firm-specific variables such as size (SIZE), book-to-market ratio (BTM), beta (BETA), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), reversal (REV), max factor (MAX) and momentum (MOM) at a monthly frequency as shown in Appendix.

Each trade in the limit order book contains the date, time, ticker, price and quantity stamps. In addition, we can track the orders on both sides of the trade via order IDs. Moreover, each trade in our sample contains a flag that helps us to identify the active side of the trade. We exclude all trades that are executed in the opening auction to account for potential heterogeneity in the information arrival. We also account for ticker changes.

The observation of the active side of the trade frees us from considering the trade initiation process. This freedom also relieves us from choosing different trade classification algorithms to assign values for (B_t, S_t). The literature on the accuracy of algorithms that classify trades as buyer or seller initiated is inconclusive. However, all classification algorithms are shown to create some bias in BIST (Aktas & Kryzanowski, 2014). Our results presented in the next section, are therefore robust to any biases that might arise due to improper selection of trade classification algorithms.

Table 1 provides the descriptive statistics for the daily buy and sell order processes for all stocks traded in BIST. We observe that the buy orders have higher variance compared to sell orders. In addition, we observe a strong positive correlation between buy and sell orders. These two findings are identical to the observations of Duarte and Young (2009), therefore we choose DY factorization in estimating the probability of informed trading. Table 2 and Table 3 provides the descriptive statistics for the firm-specific variables and the correlations among them, respectively. We observe the highest positive correlation between IVOL and MAX with 84% and the highest negative correlation between SIZE and IVOL with −26%. We observe a positive correlation between size and PIN which is in line with previous literature on the information asymmetry in BIST (Tiniç and Salih (2020); Tiniç and Savaşer (2020)).

BIST provides a natural experiment to test the impact of short selling restrictions on herding (Alkan & Guner, 2018). Temporary short-selling restrictions were put in place in Borsa Istanbul between August 2011 and July 2012. To examine the impact of short-selling restrictions on the relationship between information asymmetry and herding, we define a dummy variable D_t that takes the value 1 during the period of short-selling restrictions and 0 otherwise.

Table 1
Descriptive statistics on buy and sell order flow. In this table, we present the descriptive statistics for the cross-sectional distribution of a series of statistics based on the daily number of buy and sell observations (B_t, S_t) for each stock in our sample. The buy and sell orders are observed in our dataset which covers all stocks that are traded on BIST between March 2005 and April 2017. Our sample consists of 498 different stocks. For each stock, in each trading day, we compute the total number of buy and sell orders submitted to BIST from the intraday limit order book. Then for each stock, we compute the mean and variance of the daily buy and sell orders throughout our sample period. The first two columns represent the descriptive statistics for the mean buy and sell values in our cross-section. Similarly, the third and fourth columns represent the descriptive statistics for the variance of the daily buy and sell values. The final column represents the descriptive statistics for the Spearman correlation coefficient between the daily number of buy and sell orders.

Statistics	Mean Buy	Mean Sell	Variance Buy	Variance Sell	Correlation
Minimum	18.56	14.11	17.71	13.53	0.10
25th Perc.	248.97	182.06	355.83	229.5	0.81
Median	411.84	290.13	562.06	343.73	0.88
Mean	521.07	398.34	733.13	487.61	0.85
75th Perc.	620.56	445.17	856.33	557.30	0.92
Maximum	4627.44	4223.77	5728.53	2945.22	0.98

Table 2
Descriptive statistics on the firm-specific variables. In this table, we present the descriptive statistics for the firm-specific variables that are calculated for all stocks that are traded in BIST between March 2005–April 2017. LSV represents the herding measure of Lakonishok et al. (1992). BETA is the systematic risk factor. SIZE is the logarithm of the end of month market capitalization. BTM is the book-to-market ratio. MOM is the momentum variable. REV represents the reversal variable. ILLIQ is the illiquidity measure. MAX is the maximum daily return within a month. IVOL is the idiosyncratic volatility. PIN is the probability informed trading estimated using DY factorization. PSOS is the probability of symmetric order flow shocks.

Variable	# Obs	Mean	Standard Deviation	Minimum	Maximum
LSV	44310	0.04	0.04	−0.04	0.52
BETA	44304	0.60	0.55	−13.07	5.84
SIZE	44310	5.22	1.94	0.29	10.68
BTM	44310	1.11	1.24	0.00	53.40
MOM	43581	−0.05	0.62	−73.01	0.95
REV	43850	0.01	0.14	−0.89	2.94
ILLIQ	44310	0.00	0.07	0.00	10.01
MAX	44310	0.06	0.04	−0.10	0.20
IVOL	44304	0.02	0.01	0.00	0.18
PIN	44309	0.16	0.17	0.00	1.00
PSOS	44309	0.24	0.25	0.00	1.00

4. Fama − MacBeth regressions

The primary motivation for this study is to examine the predictive relationship between information asymmetry and future herding levels. There are competing theoretical predictions in the literature. Information cascades model predicts a positive relationship between information asymmetry and future herding whereas the investigative herding model predicts a negative relationship between information asymmetry and future herding levels. To test the impact of information asymmetry on herding, we estimate the cross-sectional regression presented in (12) for each month in our sample. That is, LSV herding measure for the full sample, along with subsamples for the buy- and sell-side herding are regressed on PIN and various firm-specific measures as in the following equation;

$$H_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}PIN_{i,t} + \lambda_{2,t}BETA_{i,t} + \lambda_{3,t}SIZE_{i,t} + \lambda_{4,t}BTM_{i,t} + \lambda'_{5,t}X_{i,t} + \varepsilon_{i,t} \tag{9}$$

where the vector $X_{i,t}$ includes other firm-specific factors such as MOM, MAX, IVOL, PSOS, and ILLIQ which are described in Appendix. We form our Hypothesis as follows;

Hypothesis 1.

$H_0: \ \lambda_{1,t} = 0$

$H_A: \ \lambda_{1,t} > 0$

To compute the standard errors, we account for both time and cross-sectional dimensions at the same time (Cameron

Table 3
Pairwise correlation among firm-specific variables. This table presents the cross-sectional correlations among time-series averages of factors. LSV represents the herding measure of Lakonishok et al. (1992). BETA is the systematic risk factor. SIZE is the logarithm of the end of month market capitalization. BTM is the book-to-market ratio. MOM is the momentum variable. REV represents the reversal variable. ILLIQ is the illiquidity measure. MAX is the maximum daily return within a month. IVOL is the idiosyncratic volatility. PIN is the probability informed trading estimated using DY factorization. PSOS is the probability of symmetric order flow shocks.

	LSV	BETA	SIZE	BTM	MOM	REV	ILLIQ	MAX	IVOL	PIN	PSOS
LSV	1										
BETA	−0.09	1									
SIZE	−0.08	0.19	1								
BTM	0.05	−0.01	−0.23	1							
MOM	−0.01	0.01	0.13	−0.21	1						
REV	−0.02	−0.05	0.06	−0.09	0.24	1					
ILLIQ	0.03	−0.01	0.00	−0.01	0.00	0.00	1				
MAX	−0.07	0.11	−0.17	0.00	−0.04	0.03	0.01	1			
IVOL	−0.03	−0.01	−0.26	0.05	−0.05	0.09	0.03	0.84	1		
PIN	0.03	0.02	0.04	−0.01	0.01	0.02	0.00	0.03	0.02	1	
PSOS	−0.02	0.07	0.13	0.00	0.00	0.01	0.00	−0.05	−0.05	−0.22	1

et al., 2011; Thompson, 2011). Our baseline Hypothesis indicates that there is no significant relationship between PIN and future herdings.

We then investigate whether the short-selling restrictions have any contemporaneous impact on the relationship between informed trading and herding by introducing a dummy, D_t, that takes value one during the period of temporary short sale restrictions in BIST that were put in place between August 2011 and July 2012, to our model.

$$H_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} PIN_{i,t} + \lambda'_{2,t} X_{i,t} + \vartheta_{1,t} D_{t+1} + \vartheta_{2,t} D_{t+1} PIN_{i,t+1} + \varepsilon_{i,t} \tag{10}$$

In our extended model, we test the Hypothesis that short-selling restrictions have no impact on the overall herding behavior as follows;

Hypothesis 2.

$H_0: \ \vartheta_{1,t} = 0$

$H_A: \ \vartheta_{1,t} > 0$

where the alternative Hypothesis indicates that herding increases under short-selling restrictions in line with Bohl et al. (2014).

The coefficient of the interaction term $D_{t+1} PIN_{i,t+1}$ enables us to observe whether the restrictions that put in place, intensifies the informational cascades or not. Therefore, in our extended model we are also able to test the null Hypothesis that short-selling restrictions have no contemporaneous impact on the relationship between informed trading and herding, as follows;

Hypothesis 3.

$H_0: \ \vartheta_{2,t} = 0$

$H_A: \ \vartheta_{2,t} > 0$

where we expect that the positive relationship between informed trading and herding strengthens as the informed investors are not able to clear out potential price misalignments (Alkan & Guner, 2018; Bohl et al., 2014).

5. Results

We present the results of the firm-level Fama-MacBeth regressions in Table 4. The dependent variable in columns (1) to (12) is the LSV herding measure for the full sample (H_{it}). The dependent variable in columns (13) and (14) is the buy-side herding measure (BH_{it}), whereas the dependent variable in columns (15) and (16) is the sell-side (SH_{it}) herding measure in line with the definitions of Wermers (1999) and Yuksel (2015). Controlling for other firm-specific factors, the impact of information asymmetry on herding is found to be positive, validating the predictions of informational cascades model in BIST. The relationship is also found significant for buy-side and sell-side herding, that is, information asymmetry leads to herd behaviour in the two sub-samples of our analysis. Bivariate regressions in columns (10) of Table 4, assert that the relationship between PIN and LSV becomes insignificant after controlling for the probability of symmetric order flow shocks. However, when we add all firm-specific factors, the statistical significance of the relationship between information asymmetry and herding persist in a multivariate setting for the whole sample. Furthermore, the relationship was found to be statistically significant for the buy-side and sell-side herding.[2]

The relationship between herding and firm characteristics such as systematic risk (BETA) and lottery stocks (MAX) is found to be symmetric for both buy-side and sell-side herding.

[2] In addition, we have conducted a univariate portfolio analysis to further explore the relationship for the buy-side and sell-side herding. The results are robust with this methodology as well. Details on the portfolio analysis can be found in Appendix.

Table 4
Results of firm-level cross-sectional regressions. This table presents the results of firm-level cross-sectional regressions. Each month, we regress the herding measures on lagged PIN estimates along with the control factors, BETA, SIZE, BTM, MOM, REV, ILLIQ, MAX, IVOL, and PSOS. Entries in the table are the time-series averages of the slope coefficients obtained from the cross-sectional regressions. Values in parenthesis present t-statistics based on double clustered standard errors (Cameron et al., 2011; Thompson, 2011). Columns (1)−(12) are for the full sample. Columns (13) and (14) are for buy-side herding and last two columns correspond to sell-side herding. We calculate buy-side and sell-side herding in line with Wermers (1999) and Yuksel (2015).

	Full Sample												Buy-Side Herding		Sell-Side Herding	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
PIN	0.003	0.004	0.004	0.003	0.004	0.003	0.003	0.003	0.003	0.002	0.005	0.005	0.005	0.005	0.004	0.003
	(2.15)	(2.44)	(2.59)	(2.25)	(2.41)	(2.22)	(2.14)	(2.31)	(2.12)	(1.45)	(3.23)	(2.86)	(2.50)	(2.47)	(1.67)	(1.60)
BETA		−0.006									−0.005	−0.005	−0.002	−0.002	−0.008	−0.008
		(−5.85)									(−4.66)	(−4.66)	(−2.55)	(−2.57)	(−5.37)	(−5.39)
SIZE			−0.002								−0.001	−0.001	−0.005	−0.005	0.002	0.002
			(−3.51)								(−2.65)	(−2.59)	(−8.96)	(−8.89)	(2.44)	(2.42)
BTM				0.002							0.001	0.001	0.001	0.001	0.000	0.000
				(2.49)							(1.61)	(1.62)	(1.74)	(1.74)	(0.52)	(0.52)
MOM					−0.002						−0.001	−0.001	0.001	0.001	0.000	0.000
					(−2.96)						(−1.30)	(−1.30)	(1.12)	(1.12)	(−0.02)	(−0.02)
REV						0.005					−0.001	−0.001	0.012	0.012	−0.011	−0.011
						(−1.33)					(−0.17)	(−0.17)	(2.73)	(2.73)	(−2.79)	(−2.79)
ILLIQ							0.026				0.093	0.093	−0.082	−0.082	0.117	0.117
							(15.16)				(5.52)	(5.51)	(−2.23)	(−2.23)	(4.28)	(4.28)
MAX								−0.039			−0.073	−0.074	−0.047	−0.047	−0.107	−0.107
								(−3.44)			(−3.99)	(−4.04)	(−2.29)	(−2.28)	(−4.30)	(−4.33)
IVOL									−0.005		0.120	0.121	−0.180	−0.180	0.497	0.498
									(−0.10)		(1.89)	(1.93)	(−2.89)	(−2.89)	(4.82)	(4.86)
PSOS										−0.003		−0.001		0.000		0.000
										(−2.43)		(−0.84)		(0.17)		(−0.23)

The stocks' overall liquidity is also turned out to be an important factor that drives future herding. Our results suggest that a 1% increase in the illiquidity of the stock will yield an average 9.3% percent increase in the future herding levels. In line with the findings of Zhou and Lai (2009), we also find that small firms tend to experience higher levels of herding. This finding might be due to professional investors who are shown to herd in small-cap stocks in BIST (Dalgıç et al., 2019, pp. 1−18). Besides, we observe past return performance proxied by momentum and reversal variables, profitability proxied by book-to-market ratio, firm-specific risk proxied by idiosyncratic volatility has no impact on future herding levels for our full sample.

In Table 4, we also show that firm-specific factors impact on buy-side and sell-side herding. For instance, sell-side herding on average *increases* by 20 bps for a 1% increase in market capitalization, whereas buy-side herding *decreases* by 50 bps for a 1% increase in market capitalization. Dalgıç et al. (2019, pp. 1−18) assert that professional (retail) investors mostly herd in small (large) stocks; therefore we can argue that sell-side (buy-side) herding is mostly due to trading activities of professional (retail) investors. We also observe different impacts of the overall liquidity of stock on buy-side and sell-side herding. We show that buy-side herding (sell-side herding) increases (decreases) with stocks overall liquidity, as expected. Recent return performance, proxied by return reversal (REV) also has an asymmetric impact over buy-side and sell-side herding. A positive return performance is attributed to higher levels of buy-side herding but lower levels of sell-side herding, as expected. Our results indicate that firms with high idiosyncratic volatility, experience low (high) levels of buy-side (sell-side) herding.[3] It has been suggested in several published work that investors tend to avoid high idiosyncratic volatile stocks (see for example, Sias (1996)). This may provide a probable reason to explain this result. That is herders may tend to herd less on the buy-side and more for the sell-side stocks.

Finally, we test the impact of short selling restrictions on the relationship between herding and using the model presented in equation (10). The results of the extended model are presented in Table 5. Results for our full sample indicate that herding levels increase on average under short-selling restrictions, as expected. In addition, the predictive power of information asymmetry on future herding levels increases by 3% under short-selling restrictions. This is in line with our expectations since the informed investors are unable to correct potential price misalignments when there are short-selling restrictions. In Table 5, we observe that the coefficient of PIN becomes insignificant after we add both the short-selling dummy D_t and the interaction term. This further underlines the importance of short-selling restrictions on the relationship between information asymmetry and herding. We observe that, in our sample period, the relationship between information asymmetry and buy-side herding is only relevant under short-selling restrictions. It may seem intuitive to suggest that during short-sell restrictions, opportunities to herd on the sell-side

[3] We believe that a more detailed analysis on the predictive relationship between IVOL and herding can provide interesting outcomes. However this analysis is beyond the scope of this paper.

Table 5
Results of the firm-level cross-sectional regressions with short sale constraints. This table presents the results of firm-level cross-sectional regressions. Each month, we regress the herding measures on lagged PIN estimates along with the control factors, BETA, SIZE, BTM, MOM, REV, ILLIQ, MAX, IVOL, and PSOS. Dt corresponds to the dummy that takes a value between August 2011 and July 2012, a period when there are short-sale restrictions in Borsa Istanbul. Entries in the table are the time-series averages of the slope coefficients obtained from the cross-sectional regressions. Values in parenthesis present t-statistics based on double clustered standard errors (Cameron et al., 2011; Thompson, 2011). Columns (1)−(2) are for the full sample. Columns (3) and (4) are for buy-side herding and the last two columns correspond to sell-side herding. We calculate buy-side and sell-side herding in line with Wermers (1999) and Yuksel (2015).

	Full Sample		Buy-Side Herding		Sell-Side Herding	
	(1)	(2)	(3)	(4)	(5)	(6)
PIN	0.004	0.004	0.004	0.004	0.004	0.004
	(2.81)	(2.79)	(2.01)	(1.95)	(1.73)	(1.73)
BETA	−0.005	−0.005	−0.003	−0.003	−0.008	−0.008
	(−4.72)	(−4.77)	(−3.05)	(−3.23)	(−5.38)	(−5.38)
SIZE	−0.001	−0.001	−0.005	−0.005	0.002	0.002
	(−2.64)	(−2.67)	(−8.63)	(−8.68)	(2.29)	(2.29)
BTM	0.001	0.001	0.001	0.001	0.000	0.000
	(1.67)	(1.70)	(1.70)	(1.75)	(0.43)	(0.44)
MOM	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.11)	(−0.99)	(−0.78)	(−0.61)	(−0.69)	(−0.67)
REV	0.000	0.000	0.004	0.005	−0.003	−0.003
	(−0.09)	(−0.02)	(0.84)	(0.93)	(−0.88)	(−0.86)
ILLIQ	0.000	0.000	0.000	0.000	0.000	0.000
	(5.52)	(5.52)	(−1.82)	(−1.78)	(4.67)	(4.67)
MAX	−0.073	−0.073	−0.048	−0.047	−0.095	0.095
	(−4.04)	(−4.00)	(−2.04)	(−1.98)	(−4.25)	(−4.24)
IVOL	0.119	0.116	−0.137	−0.138	0.386	0.386
	(1.89)	(1.83)	(−1.88)	(−1.88)	(4.30)	(4.29)
PSOS	−0.001	−0.001	−0.001	−0.001	0.000	0.000
	(−0.97)	(−1.01)	(−0.83)	(−0.90)	(−0.28)	(−0.28)
D_t		0.008		0.016		0.001
		(3.86)		(5.37)		(0.69)
PIN*D_t	0.030	0.007	0.062	0.015	0.004	0.000
	(3.98)	(1.47)	(6.33)	(2.79)	(0.55)	(0.06)

will be limited, which may explain highly insignificant result for the interactive dummy in our extended model. The informed traders have limited opportunity to clear away price distortions due to the restrictions (Alkan & Guner, 2018; Bohl et al., 2014). It also seems plausible to assume that the informed traders will be trading more on the buy-side during the period when these restrictions have been in place. Higher trading activity by informed traders on the buy-side may prompt more herding on the buy-side.

In sum, we reject our baseline Hypothesis that information asymmetry has no explanatory power in explaining future herding levels. We show that information asymmetry proxied by the PIN has significant explanatory power even after controlling for other firm-specific factors. However, this relationship is asymmetric where the role of information asymmetry is more evident in the buy-side herding.

Next, we test the null Hypothesis that short-selling restrictions have no contemporaneous impact on herding activity. Similarly, we reject this hypothesis and show that herding levels increase on average under short-selling restrictions. Specifically, we show informational cascades are predominantly evident for buy-side herding under short-selling restrictions.

One of the primary objectives of the paper has been to examine the validity of the relationship between herding and information asymmetry. Even though our main results support the predictions of information cascades theory which *assumes uninformed investors follow informed investors,* a major drawback of our analysis is that we cannot identify whether the herding can be attributed to informed or uninformed investors.[4] To that end, our results have to be interpreted in caution; we can only identify the predictions of the information cascades theory but not its assumption. While interpreting our results and drawing conclusions for BIST, we shall therefore, *assume* that herding is primarily done by uninformed investors and therefore may contribute to behavioral herding in Borsa Istanbul.

6. Conclusions

This study examines the relationship between information asymmetry and herding for all stocks traded in Borsa İstanbul between March 2005 and April 2017. There are competing views on the impact of informed trading on future herding levels. The informational cascade Hypothesis argues that investors disregard their private information and follow others when there is high information asymmetry in the market (Bikhchandani et al., 1992; Wermers, 1999). This worldview expects herding levels to rise when there is more information asymmetry for a stock. Investigative herding, on the other hand, expects a convergence in the investment strategies of investors that read the same information (Sias, 2004). This implies that when everybody in the market has the same information (low information asymmetry) the herding levels rise.

In this paper, we investigate the predictive power of informed trading on future herding levels. Our baseline results indicate that informed trading increases future herding levels even after we control for other firm-specific characteristics. However, we show that the information cascades are relevant only for buy-side herding, where the persistence in the order flow is generated mostly by non-professional investors (Dalgıç et al., 2019, pp. 1−18).

Turkish market also provides a natural experiment to examine the impact of short-selling restrictions on the relationship between information asymmetry and herding. We extend our analysis and show that average herding levels increase under short-selling restrictions. Finally, we show informational cascades are predominantly evident for buy-side herding under short-selling restrictions.

Overall our results are consistent with the previous findings documented by Zhou and Lai (2009) and Alhaj-Yaseen and Rao (2019), which argue that informational cascades can be the driving factor of the herding in the equity markets. Contrary to these studies, we show that the informational cascades

[4] We thank the anonymous referee for pointing this out.

Hypothesis is valid only for buy-side herding for our sample period. Besides, we show that short-selling restrictions may be the driving factor of buy-side herding in equity markets.

Declaration of Competing Interest

None.

Appendix.

- **Variable Definitions (A1)**

SIZE: Firm size for a given month is taken to be the natural logarithm of the firms' market value, that is, the end of month price times the number of shares outstanding.

BOOK-TO-MARKET RATIO: Book to market ratio for a firm is taken to be the ratio of the firms' end of month total equity value to its market value.

BETA: We estimate the market risk of given stock i, on a given month t, from the market model given below;

$$R_{id} = \alpha_i + \beta_i R_{md} + e_{id} \quad d = 1 \ldots D_t$$

Where D_t is the number of trading days on month t. R_{id} is the daily return on the stock i on a given day d. Similarly, we take R_{md} to be the return of the BIST100 index of a given day d. We estimate the above equation for each stock using daily returns within a month.

IDIOSYNCRATIC VOLATILITY: We measure the idiosyncratic risk of a stock from the standard deviation of the daily residuals, presented in the above equation. That is,

$$IVOL_{it} = \sqrt{var(e_{id})}$$

ILLIQUIDITY: We measure stock illiquidity for each month t, with the ratio of the absolute monthly stock return to its trading volume, similar to Amihud (2002).

$$ILLIQ_{it} = |R_{it}|/VOL_{it}$$

REVERSAL: We define the reversal variable for each stock in month t as the return on the stock over the previous month, similar to Jegadeesh (1990).

MOMENTUM: We define the momentum variable for each stock in month t as the cumulative percentage return over the last six months. That is;

$$MOM_{it} = \frac{P_{it-1} - P_{it-7}}{P_{it-7}}$$

where P_{it} is the price of the stock at the end of month t.

MAX: We define the maximum Daily return within a month as:

$$MAX_{it} = \max(R_{id}), \qquad d = 1 \ldots N_t$$

where N_t is the number of trading days on month t. R_{id} is the Daily return on stock i on a given day d.

- **Estimation procedure of the probability of informed trading (A2)**

The likelihood presented in equation (6) (EKOP factorization) is prone to several problems.[5] The first problem, labeled as the "floating-point exception", originates from the shrinkage of the feasible solution set for the non-linear optimization problem as the daily number of buy and sell orders increase. The optimal likelihood value becomes undefined for large enough (B_t, S_t) whose factorials cannot be computed by mainstream computers (Easley et al. (2010); Lin & Ke, 2011).

To deal with this problem, Duarte and Young (2009) extends the EKOP factorization by replacing $\exp(-\varepsilon_b)\frac{(\varepsilon_b)^{B_t}}{B_t!}$ with $\exp(-\varepsilon_b + B_t\log(\varepsilon_b) - \sum_{i=1}^{B_t}\log(i))$ and other components of the likelihood with similar modifications.

The second problem is due to boundary solutions. Yan and Zhang (2012) show that the parameter estimates $\widehat{\alpha}$ and $\widehat{\delta}$ falls onto the boundaries of the parameter space [0,1] when estimating PIN. They argue that the problem of boundary solutions occur since the maximum likelihood algorithm gets stuck at a local optimum. PIN estimate that is presented in equation (8) is directly related to the estimate of α, that is, letting α equal to zero will directly equate the PIN estimate to zero as well. This can be problematic on studies that estimate PIN over a certain period in which an information event has definitely occurred. For example, for studies that estimate PIN over a quarter, one can be sure that there is at least one information event; earnings announcement.

To overcome the problems due to boundary solutions, Yan and Zhang (2012) propose a grid-search algorithm (YZ-algorithm) that spans the parameter space for 125 different sets of initial parameter values. For each of the initial parameter vector, YZ algorithm obtains different parameter estimates and select the estimate that gives the highest likelihood value for non-boundary solutions.

The sequential trading model of Easley et al. (1996) also enforces a negative contemporaneous correlation between the number of buy and sell orders (B_t, S_t). Informed trading can inflate the number of buys and sell orders, separately. Duarte and Young (2009) shows the contemporaneous covariance between the buy and sell order flow as follows;

$$cov(B_t, S_t) = (\alpha\mu)^2(\delta - 1)\delta \leq 0 \tag{11}$$

This aspect of the PIN models contradicts with the empirical findings of several studies. Duarte and Young (2009) documents a strong positive correlation between buy and sell orders for stocks that trade in U.S. equity markets.

To account for the positive correlation between the buy and sell order arrival processes, they define another event that causes both buy and sell order flow to increase. They called this event a *symmetric order-flow shock*. When there is no

[5] See Celik and Tiniç (2018) for a detailed literature review on the problems with estimating PIN.

information event, the probability of such an event is assumed to follow a Bernoulli distribution with parameter γ. The probability of symmetric order-flow shock (PSOS) conditional on the arrival of private information is also assumed to follow a Bernoulli distribution but with a different parameter, γ'. In case of a symmetric order flow shock, the additional arrival rate of buys (sells) is defined by the parameter $\phi_b(\phi_s)$.

Then the parameter vector of the extended model becomes, $\theta = \{\alpha, \delta, \gamma, \gamma', \mu_b, \mu_s, \varepsilon_b, \varepsilon_s, \phi_b, \phi_s\}$ The joint probability function in equation (5) can be updated as follows;

The problem of boundary solutions is also evident for estimating PIN when DY factorization is used. To this end, we choose 10 different random starting points for ($\alpha^0, \delta^0, \gamma^0, \gamma'^0$) from the uniform distribution U(0,1) for parameters that are bounded from above and below. For parameters that are bounded only from above, ($\mu_b^0, \mu_s^0, \varepsilon_b^0, \varepsilon_s^0, \phi_b^0, \phi_s^0$), we set the arrival rates to be the one-third of the respective buy and sell values within the specified period.

$$
\begin{aligned}
f(\mathrm{B_t}, S_t|\theta) \equiv\ & (1-\alpha)(1-\gamma)\exp\left[-\in_b + B_t\log(\in_b) - \sum_{i=1}^{B_t}\log(i)\right]\exp\left[-\in_S + S_t\log(\in_S) - \sum_{i=1}^{S_t}\log(i)\right] \\
& + (1-\alpha)\gamma\exp\left[(-\in_b+\phi_b) + B_t\log(\in_b+\phi_b) - \sum_{i=1}^{B_t}\log(i)\right]\ \exp\left[(-\in_s+\phi_s) + S_t\log(\in_s+\phi_s) - \sum_{i=1}^{S_t}\log(i)\right] \\
& + \alpha(1-\delta)(1-\gamma\prime)\exp\left[(-\in_b+\mu_b) + B_t\log(\in_b+\mu_b) - \sum_{i=1}^{B_t}\log(i)\right]\ \exp\left[-\in_S + S_t\log(\in_S) - \sum_{i=1}^{S_t}\log(i)\right] \\
& + \alpha(1-\delta)\gamma\prime\exp\left[(-\in_b+\phi_b+\mu_b) + B_t\log(\in_b+\phi_b+\mu_b) - \sum_{i=1}^{B_t}\log(i)\right]\ \exp\left[(-\in_s+\phi_s) + S_t\log(\in_s+\phi_s)\right. \\
& \left. - \sum_{i=1}^{S_t}\log(i)\right]\ + \alpha\delta(1-\gamma\prime)\exp\left[-\in_b + B_t\log(\in_b) - \sum_{i=1}^{B_t}\log(i)\right]\ \exp\left[(-\in_s+\mu_s) + S_t\log(\in_s+\mu_s) - \sum_{i=1}^{S_t}\log(i)\right] \\
& + \alpha\delta\gamma\exp\left[(-\in_b+\phi_b) + B_t\log(\in_b+\phi_b) - \sum_{i=1}^{B_t}\log(i)\right]\ \exp\left[(-\in_s+\phi_s+\mu_s) + S_t\log(\in_s+\phi_s+\mu_s) - \sum_{i=1}^{S_t}\log(i)\right]
\end{aligned}
\tag{10}
$$

The structural model presented in equation (10), enables a positive correlation between buy and sell order flow. Then, the probability of informed trading adjusted for the symmetric order flow shocks is given by;

$$
\mathrm{AdjPIN} = \frac{\alpha(\delta\mu_s + (1-\delta)\mu_b)}{\alpha(\delta\mu_s + (1-\delta)\mu_b) + (\phi_b+\phi_s)(\alpha\gamma' + (1-\alpha)\gamma) + \varepsilon_b + \varepsilon_s} \tag{12}
$$

and the probability of symmetric order flow shock (PSOS) is then given by;

$$
PSOS = \frac{(\phi_b+\phi_s)(\alpha\gamma' + (1-\alpha)\gamma)}{\alpha(\delta\mu_s + (1-\delta)\mu_b) + (\phi_b+\phi_s)(\alpha\gamma' + (1-\alpha)\gamma) + \varepsilon_b + \varepsilon_s} \tag{13}
$$

- **Univariate portfolio analysis (A3)**

To measure the buy demand (sell-demand) we have constructed the order imbalance measure (OIB) of Chordia et al. (2002). For a given stock *i,* in a given month *t,* OIB is given by;

$$OIB_{i,t} = \frac{B_{i,t} - S_{i,t}}{B_{i,t} + S_{i,t}}$$

To that end, we have also measured order imbalance for each month and for each stock in our sample. We then sort stocks in our sample each month according to their PIN measures. We have calculated the average buy herding measure along with the order imbalance for the stocks that are in the highest and lowest 10% quantiles.

Let $\overline{LSV_t^H}, \overline{LSV_t^L}$ respectively show the average buy herding measure for the high and low group for a given month t. Similarly, let $\overline{OIB_t^H}$ and $\overline{OIB_t^L}$ indicate the average order imbalance measure of the high and low group for a given month t, respectively. Finally, let $\overline{R_t^H}$, $\overline{R_t^L}$ denote the cross-sectional averages in the high and low group for a given month t, respectively. Then we have tested the statistical significance of the time-series of the *differences* in these averages $[\overline{LSV_t^D} = \overline{LSV_t^H} - \overline{LSV_t^L}; \overline{OIB_t^D} = \overline{OIB_t^H} - \overline{OIB_t^L}; \overline{R_t^D} = \overline{R_t^H} - -\overline{R_t^L}]$ in order to test the relationship between buy demand, herding and informed trading, as suggested. That is,

Hypothesis 4.

$$H_0 : \overline{LSV_t^D} = 0$$

$$H_A : \overline{LSV_t^D} > 0$$

Hypothesis 5.

$$H_0 : \overline{OIB_t^D} = 0$$

$$H_A : \overline{OIB_t^D} > 0$$

Hypothesis 6.

$$H_0 : \overline{R_t^D} = 0$$

$$H_A : \overline{R_t^D} \neq 0$$

We compute the t-statistic over our sample period to test the Hypothesis 4 and 5.

The results of our univariate analysis are provided in Table A1. Our results first indicate that the differences in PIN between the top and bottom ten percent is significantly different from zero. In addition, we observe that contemporaneous buy herding is significantly higher for the stocks with high information asymmetry. Similarly, contemporaneous buy demand, proxied by the order imbalance is also higher for stocks with high information asymmetry. Finally, we show that the differences in cross-sectional means of returns is significantly different from zero. This further supports our results presented in the revised manuscript about the predictive relationship between information asymmetry and herding. To that end, we can argue that stocks with high information asymmetry tend to have higher levels of herding, in line with the expectations of informational cascades theory, both for the buy-side and sell-side herding.

Table A1
Results of the univariate portfolio sorting based on PIN. In this table we provide the results for our univariate portfolio tests. At the beginning of each month we sort the stocks in our sample with respect to their PIN measures. We determine the high-PIN (low-PIN) group as the stocks that are in the top (bottom) 10% quantile. Let $\overline{LSV_t^H}, \overline{LSV_t^L}$ respectively show the average buy herding measure for the high and low group for a given month t. Similarly, let $\overline{OIB_t^H}$ and $\overline{OIB_t^L}$ indicate the average order imbalance measure of the high and low group for a given month t, respectively. First column represents whether the differences in PIN between high and low group is significant throughout our sample. Second column provides the results for the test of Hypothesis 4. Third column provides the results for the test of Hypothesis 5. Last column provides the results for the test of Hypothesis 6. The first row provides the estimate for the time-series average for the average difference. Second row provides the one-way t-statistics. Third row provides the p-value. P.

	$\overline{\overline{PIN^D}}$	$\overline{\overline{LSV^D}}$	$\overline{OIB^D}$	$\overline{R^D}$
Panel A: Buy side				
Estimate:	0.51	0.01	0.01	−0.01
t-statistic:	200.66	5.79	5.48	−2.48
p-value:	(0.00)	(0.00)	(0.00)	(0.01)
Panel B: Sell side				
Estimate:	0.52	0.004	−0.01	0.001
t-statistic:	194.66	3.90	−3.29	0.25
p-value:	(0.00)	(0.00)	(0.00)	(0.80)

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