Investor Attention, News and the Herd Behavior of Individual Stock Returns

Nilakshi Borah, Cedric Mbanga, and Suzanne Shoukfeh *

Abstract

Purpose: This paper examines the herd behavior of individual returns around their industry average in stressful market condition, when industry-wide investor attention is high or low, and when good or bad industry-wide news reach the market.

Design/Methodology: Decile portfolios are formed based on proxies of aggregate market condition, industry-wide level of investor attention and industry-wide news signal. Indicator variables identifying the months in the highest and lowest portfolios are then entered in regression tests to capture the degree to which returns herd around their industry. Both cross-sectional and absolute deviations from industry average are used to measure herding.

Findings: The analysis reveals that for the majority of industries, herding exist in calm market conditions. Moreover, herding appears to be concentrated in months where the industries record abnormally low returns and in months in which the industries receive good news.

Practical Implications: Understanding what drives the herd behavior of individual returns in financial markets portfolio may be of particular value to investment companies, such as hedge funds, who seek to time the market.

Originality/Value: The paper offers new insights on the drivers of herding in financial markets. While prior studies focus on examining herding in market turmoil, this paper documents herding around extreme events and following news arrival.

JEL Classification: G14, G15, C22
Keywords: Herding, Extreme Returns, Investor Attention, Good News, Bad News

I Introduction

Herding in financial markets is characterized by the tendency of investors to copy each other or replicate the behavior of the aggregate market. This phenomenon has increasingly attracted the attention of researchers, practitioners and regulators over the past decade. In fact, researchers have examined the herding effect in various aspects of financial markets, including in the equity market (Christie and Huang 1995; Chang, Cheng, and Khorana 2000; Hwang and Salmon 2004; Tan et al. 2008; Chiang, Li, and Tan 2010; Economou, Kostakis, and Philippas 2011), the fixed income market (Galariotis et al. 2016), the commodities market (Gleason, Lee, and Mathur 2003; Philippas 2014), the ETFs (Gleason, Mathur, and Peterson 2004) and mutual fund markets (Lakonishok, Shleifer, and Vishny 1992; Wermers 1999; Sias 2004) among others. Spyrou (2013) offers an

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extensive review of theory and empirical results on the effect of herding in financial markets spanning the last two decades.

While there exists some consensus on the existence of herding in emerging economies (Kallinterakis and Kratunova 2007; Economou, Hassapis and Philippas 2018), findings in this context are generally thought to be driven by the endogenous characteristics of those markets, including low trading volume, insufficient regulatory frameworks, information asymmetries and quasi-nonexistence of transparency and information disclosure. In developed economies however, the evidence is mixed. Although theoretical underpinnings of herding in financial markets predict the prevalence of herding during market downturns, empirical evidence is either absent (Christie and Huang 1995; Chang, Cheng, and Khorana 2000), more pronounced in market downturns (Demirer, Kutan, and Chen 2010; Chiang and Zheng 2010; Chen 2013; Philippas et al. 2013; Mobarek, Mollah, and Keasey 2014), or primarily evident in bull markets (Tan et al. 2008; Economou, Kostakis, and Philippas 2011; Economou et al. 2015). Jiang et al. 2022 investigate herding behavior triggered by the COVID-19 outbreak in 2020 by considering six typical Asian stock markets by employing cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) and shows a clear presence of herding in the "Feb 2020-Jan 2021" time window. Hasan et al. 2023 provides new evidence of herding due to non- and fundamental information in 33 global equity markets. Using quantile regressions applied to daily data for 33 countries, Hasan et al. 2023 investigate herding during the Eurozone crisis, China's market crash in 2015–2016, in the aftermath of the Brexit vote and during the Covid-19 Pandemic and find significant evidence of herding driven by non-fundamental information in case of negative tail market conditions for most countries.

In this paper, we revisit the herding behavior of individual stock returns in the US equity market around their industry average. We perform "out-of-sample" tests of the evidence reported by Christie and Huang (1995) using alternative definitions of market conditions. Specifically, we employ the CBOE Volatility Index (VIX) as well as the St. Louis Federal Reserve Financial Stress Index (FSI) as proxies for market condition. For the majority of industries considered (about 75% of the industries on average), we find evidence that herding appears to exist in months where VIX or FSI are at their lowest. In other words, individual stock returns herd around their industry average in calm, not stressful market conditions. In stressful markets, periods of high VIX or high FSI, we find no evidence of individual stock return herding around their industry average for all the industries considered. This finding is consistent with Christie and Huang (1995) and Chang, Cheng, and Khorana (2000), among others.

Barber and Odean (2007) report evidence that individual investors are net buyers of attention-grabbing stocks, defined as those experiencing extreme one-day returns. Also, Bali, Cakici and Whitelaw (2011) find that investors exhibit a preference for stocks with extreme positive returns. These studies raise the possibility that factors other than market condition may induce herding, including the occurrence of extreme returns (e.g., an attention grabbing-event). We therefore explore herd behavior of individual stock returns in months when the industry attracts significant attention based on their recording of unusually high or low returns. We generally find that herding is concentrated in months in which the industries record their worst average daily returns, suggesting that herding is present in industries that attract attention for earning negative returns.

To explore this intuition further, we ask the question of whether individual stock returns herd around their industry average following the arrival of industry-wide good or bad news. Interestingly, we find that the behavioral models of Scharfstein and Stein (1990), Banerjee (1992), Bikhchandani, Hirshleifer, and Welch (1992), Trueman (1994), and Hirshleifer, Subrahmanyam, and Titman (1994) all predict a form of herd behavior of investors based on news arrival, private or otherwise. In this paper, we do not only explore, ex-post, the herd behavior of individual stock returns based on news arrival, but also based on the signal (good or bad) sent to the market by the arrival of news. Using the industry level average stock distance to the fifty-two-week high to capture the arrival of good or bad news as in George and Hwang (2004), we find that herding is concentrated in months in which the industries receive good news and not bad news.

Our study contributes to the literature in a few ways. First, we offer fresh evidence of the herd behavior of individual stock returns around their industry average in calm, not necessarily bull markets, rather than stressful market conditions. Next, we document the herd behavior of individual stock returns in months in which the average firm in the industry records extreme negative rather than positive returns, and in months in which average firm in the industry receives good rather than bad news. To the best of our knowledge, we are the first to document these latter findings. Ultimately, we offer new insight, relevant to academics, practitioners and regulators on the herd behavior of individual stock returns in financial markets.

The remainder of this paper is organized as follows: Section 2 describes the data and method employed, Section 3 presents empirical results and discussions, and Section 4 offers concluding remarks.

II Data and Method

Our sample builds on every listed security on the Center for Research in Security Prices (CRSP) data files with share codes 10 or 11 from January 1990, to December 2014. We obtain daily prices, returns, SIC codes and market capitalization from the CRSP data files. From Bloomberg, we collect data on the volatility index (VIX) and the St. Louis Federal Reserve Financial Stress Index (FSI). Finally, as is common in the finance literature, we restrict our sample to stocks priced between \$5 and \$1000 U.S dollars.

It is common in the finance literature to build on the Standard Industrial Classification (SIC) scheme to classify firms into industry groups. Established in the United States (U.S.) back in 1937, the SIC scheme groups into an industry companies with comparable production processes or whose products are used or distributed together (see Economic Classification Policy Committee 1994, Chan, Lakonishok and Swaminathan 2007). However, with challenges to the effectiveness of this classification scheme based on the growing importance of services and changes in the technology landscape among others (see Clarke 1989, Fama and French 1997) reorganizes the SIC codes to offer a series of alternative classification systems that are considered the go-to-classification schemes in accounting, finance and economic literatures.

This Fama and French industry classification (FFIC) has been extensively used in accounting (see, Chan, Frankel, and Kothari 2004; Francis, LaFond, Olsson, and Schipper 2005; Richardson 2006), finance (see, Brennan, Wang, and Xia 2004; Daniel and Titman 2006; Ferson and Harvey 1999; Hong, Torous, and Valkanov 2007; Moskowitz and Grinblatt 1999; Pastor and Stambaugh 1999; Purnanandam and Swaminathan 2005, Flannery and Rangan 2006; Graham and Kumar 2006), and economics (see., Bebchuk and Grinstein 2005; Wulf 2002). From the Kenneth French data library, we obtain the Fama and French 12-industry SIC classification that we then use to classify the stocks in our sample.

Next, we follow Christie and Huang (1995) and Hwang and Salmon (2004) among others to compute for every industry portfolio the monthly cross-sectional standard (CSSD) and absolute (CSAD) deviation of return as follows:

$$CSSD_{j,t} = \left[\sum_{i=1}^{i=N} \frac{\left(R_{i,t,j} - \bar{R}_{j,t}\right)^2}{N-1}\right]^{\frac{1}{2}} \tag{1}$$

$$CSAD_{j,t} = \sum_{i=1}^{i=N} \frac{\left|R_{i,t,j} - \bar{R}_{j,t}\right|}{N-1} \tag{2}$$

where $R_{i,t,j}$ is the value-weighted return of stock *i* in month *t* belonging to the industry j. $\bar{R}_{j,t}$ is cross-sectional average of the N returns in industry j. Christie and Huang (1995) and Hwang and Salmon (2004) argue that these measures (CSSD and CSAD) quantify the degree to which individual returns move in concert with the industry return, and therefore capture the key attribute of herd behavior. Therefore, herding is observed, ex-post, if stressful market condition (VIX or FSI) negatively predicts the dispersion of individual returns around their respective industry returns (CSSD and CSAD).

We also examine the question of whether individual stock returns herd around their industry average following the arrival of good and bad news. George and Hwang (2004) (GH henceforth) argue that stocks whose current prices are near (far) from their fifty-two-week high are those for which good (bad) news recently reached the market. To proxy for the arrival of industry wide good or bad news, we compute each industry's GH ratio as the average of the individual stock distance to their respective fifty-two-week high prices (IGH).

$$GH_{i,t} = \frac{Price_{i,t}}{52WH_{\ i,t}} \tag{3}$$

$$IGH_{j,t} = \sum_{i=1}^{\mathrm{i=N}} \frac{GH_{i,t,j}}{N} \tag{4}$$

George and Hwang (2004) report evidence consistent with the notion that proximity of stock's current price to the 52-week high price generates investor underreaction and subsequent return continuation. We use GH ratio to measure the proximity to the 52-week high price, defined as the ratio of a stock's current price to its 52-week high price. The higher values of GH measure suggest that current price is closer to the 52-week high price. Again, in the extreme, if the formation month end price is the 52-week high price, then the GH measure has the maximum possible value of 1.

Finally, we consider the possibility that individual stock returns herd around their industry average when the industry attracts considerable attention, for positive or negative reasons. To proxy for attention grabbing events, we compute for every month and for each industry an average maximum and minimum daily returns following Barber and Odean (2007) and Bali, Cakici and Whitelaw (2011). Table 1 reports the time series average of our key variables across all industries.

Table 1. Time Series Averages of Key Variables

This table reports the time series average of the key variables for each of the twelve industries considered over the period going from January 1990 to December 2014. CSSD is the average firm-level cross-sectional standard deviation of returns, capturing return variability around the industry average. CSAD is the average firm-level cross-sectional absolute deviation of returns around the industry average. MAXRET is the average monthly firm-level maximum daily return for the industry and MINRET is the average monthly firm-level minimum daily return for the industry. IGH is the monthly industry average firm-level price distance to the 52-Week high price.

Industry	Firms	CSSD	CSAD	MAXRET	MINRET	IGH
1	338	2.295	2.298	0.049	-0.041	0.833
2	158	3.333	3.335	0.061	-0.052	0.789
3	602	1.702	1.704	0.056	-0.048	0.808
4	287	3.364	3.370	0.054	-0.047	0.817
5	125	2.098	2.107	0.055	-0.047	0.816
6	1098	2.991	2.993	0.077	-0.063	0.743
7	212	2.398	2.404	0.064	-0.053	0.792
8	170	3.314	3.324	0.034	-0.030	0.882
9	631	2.124	2.125	0.066	-0.056	0.775
10	602	2.669	2.671	0.080	-0.064	0.741
11	2274	2.266	2.267	0.054	-0.046	0.840
12	1006	1.476	1.477	0.077	-0.062	0.761

III Empirical Results

Herding and Market Condition

Our empirical exercise follows Christie and Huang (1995) and Hwang and Salmon (2004). Specifically, we estimate the following general models:

$$CSSD_{j,t} = \alpha + \beta^{Stress} D_{j,t}^{Stress} + \beta^{Calm} D_{j,t}^{Calm} + \varepsilon_{j,t} \quad (5)$$

$$CSAD_{j,t} = \alpha + \beta^{Stress} D_{j,t}^{Stress} + \beta^{Calm} D_{j,t}^{Calm} + e_{j,t} \quad (6)$$

where CSSD and CSAD are defined and computed as described earlier. $D_{j,t}^{Stress}$ is an indicator variable that takes the value of one for months in which the variable under consideration (VIX or FSI) is in the top decile of months sorted based on the VIX or FSI respectively; and zero otherwise. $D_{j,t}^{Calm}$ is an indicator variable that takes the value of one for months in which the variable under consideration (VIX or FSI) is in the bottom decile of months sorted based on the VIX or FSI respectively; and zero otherwise. For example, when examining the herding behavior of individual stock returns in stressful market conditions – using the VIX [FSI] to proxy for market condition, $D_{j,t}^{Stress}$ is labeled HVIX [HFSI] and takes the value of one for months in the highest decile of months sorted based on the volatility [financial stress] index and zero otherwise. Similarly, $D_{j,t}^{Calm}$ is labeled LVIX [LFSI] and takes the value of one for months in the lowest decile of months sorted based on the volatility [financial stress] index and zero otherwise. This approach allows us to capture both tails of the distribution of our proxies for market condition.

As pointed by Christie and Huang (1995), rational asset pricing models predict that individual returns dispersion should be higher in stressful market conditions. However, the herding of individual returns is displayed through a reduction of return dispersion under similar market conditions. In the context of this study, unusually stressful market conditions occur when the volatility index (VIX) or the Financial Stress Index (FSI) are at their highest; that is during those months in which the VIX or FSI rank in the highest decile of months sorted based on the VIX or FSI respectively. In contrast, unusually calm market conditions occur when the volatility index (VIX) or the Financial Stress Index (FSI) are at their lowest; that is during those months in which the VIX or FSI rank in the lowest decile of months sorted based on the VIX or FSI respectively. Under these conditions, a finding of positive and significant β^{Stress} or β^{Calm} will be seen as consistent with rational asset pricing models, whereas negative and significant β^{Stress} or β^{Calm} will be seen as evidence of herding for the given industry.

Using the Volatility Index

Table 2 reports the results of our estimation of equations (5) in Panel A and equation (6) in Panel B. In Panel A, we find that for eight out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly increases with market stress (β^{Stress} are positive and statistically significant). This finding is consistent with Christie and Huang (1995) who find no evidence of herding in stressful market conditions. Our findings are also consistent with traditional asset pricing models that suggests that market stress increase return dispersions. However, we also find that for nine out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly decreases when market stress is at its lowest (coefficients for β^{Calm} are negative and statistically significant). For example, we find that for the Consumer Non-Durables (1) and Utilities (8) industries, both β^{Calm} are -1.08 and -0.97 with t-statistics of -4.31 and -2.70 respectively. This evidence is consistent with the existence of individual stock return herding in nine out of twelve industries, particularly in good or “calm” market conditions.

Using the cross-sectional absolute return dispersion (CSAD), we find in Panel B of Table 2 evidence consistent with those reported in Panel A. While CSAD increases in stressful market conditions, it decreases when the volatility index is at its lowest, exhibiting apparent herding behavior. Similar to our results in Panel A, we find that the herding behavior of individuals is observed in nine out of twelve industries.

Using the Financial Stress Index

To add robustness to our earlier findings, we re-estimate equations (5) and (6) using the St. Louis Federal Reserve Financial Stress Index (FSI) to proxy for market conditions. We report the results of this exercise in Table 3. In Panel A of Table 3, we find that for eleven out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly increases with market stress (coefficients for β^{Stress} are positive and statistically significant). However, we also find that for ten out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly decreases when the financial stress index is at its lowest (coefficients for β^{Calm} are negative and statistically

Table 2. Using VIX as Indicator of Market Condition

This table reports regression estimates for each industry of equations (3) and (4) over the entire sample period: January 1990 to December 2014. In Panel A. CSSD is defined as earlier and used as dependent variable. In Panel B, CSAD is defined as earlier and used as dependent variable. HVIX is an indicator variable for months in the highest decile of months ranked based on the volatility index (VIX). LVIX is an indicator variable for months in the lowest decile of months ranked based on the volatility index (VIX). We report robust M-Estimation regression estimates using Huber (1964) weight with c = 1.345. T-Statistics are provided in parentheses below the respective coefficients. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels.

Panel A: CSSD												
Industries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HVIX	1.15**	1.83*	1.12***	0.51	0.50	1.04	1.26**	2.06***	0.72*	0.82	1.08**	0.71***
β^{Stress}	(2.55)	(1.77)	(2.77)	(1.19)	(1.13)	(1.56)	(2.26)	(2.96)	(1.92)	(1.53)	(2.29)	(2.71)
LVIX	**-1.08*** **	**-0.92*** *	**-0.39***	**-1.09*** *	**-0.55*** *	**-0.82*** *	**-0.56*** *	**-0.97*** **	*-0.15*	*-0.53*	*-0.48*	**-0.60*** **
β^{Calm}	**(-4.31)**	**(-2.12)**	**(-1.87)**	**(-2.56)**	**(-2.31)**	**(-1.98)**	**(-2.29)**	**(-2.70)**	*(-0.53)*	*(-1.38)*	*(-1.52)*	**(-3.94)**
cons	2.25***	3.21***	1.61***	3.40***	2.09***	2.94***	2.30***	3.17***	2.06***	2.62***	2.19***	1.45***
	(16.49)	(18.38)	(18.53)	(17.26)	(15.85)	(16.61)	(19.43)	(17.64)	(18.69)	(17.83)	(16.15)	(19.51)
R^2	0.0514	0.0403	0.0633	0.0145	0.0124	0.0214	0.0469	0.0604	0.0179	0.0172	0.0306	0.0590
adj. R^2	0.0450	0.0339	0.0570	0.0078	0.0057	0.0148	0.0404	0.0541	0.0113	0.0105	0.0241	0.0527
Panel B: CSAD												
HVIX	1.16**	1.84*	1.12***	0.51	0.50	1.04	1.26**	2.07***	0.72*	0.82	1.08**	0.71***
β^{Stress}	(2.56)	(1.77)	(2.77)	(1.19)	(1.13)	(1.56)	(2.26)	(2.96)	(1.92)	(1.53)	(2.29)	(2.71)
LVIX	**-1.08*** **	**-0.92*** *	**-0.39***	**-1.09*** *	**-0.55*** *	**-0.83*** *	**-0.56*** *	**-0.97*** **	*-0.15*	*-0.53*	*-0.48*	**-0.60*** **
β^{Calm}	**(-4.31)**	**(-2.12)**	**(-1.87)**	**(-2.56)**	**(-2.31)**	**(-1.98)**	**(-2.28)**	**(-2.70)**	*(-0.53)*	*(-1.39)*	*(-1.52)*	**(-3.94)**
cons	2.26***	3.22***	1.61***	3.40***	2.10***	2.94***	2.31***	3.18***	2.06***	2.62***	2.19***	1.45***
	(16.49)	(18.38)	(18.53)	(17.26)	(15.86)	(16.61)	(19.44)	(17.63)	(18.69)	(17.83)	(16.15)	(19.51)
N	300	300	300	300	300	300	300	300	300	300	300	300
R^2	0.0514	0.0404	0.0633	0.0145	0.0124	0.0214	0.0468	0.0604	0.0180	0.0172	0.0306	0.0590
adj. R^2	0.0450	0.0340	0.0570	0.0078	0.0057	0.0148	0.0404	0.0541	0.0113	0.0105	0.0241	0.0527

Table 3. Using FSI as Indicator of Market Condition

This table reports regression estimates for each industry of equations (3) and (4) over the entire sample period: January 1990 to December 2014. In Panel A. CSSD is defined as earlier and used as dependent variable. In Panel B, CSAD is defined as earlier and used as dependent variable. HFSI is an indicator variable for months in the highest decile of months ranked based on the St. Louis Federal Reserve Financial Stress Index (FSI). LFSI is an indicator variable for months in the lowest decile of months ranked based on the St. Louis Federal Reserve Financial Stress Index (FSI). We report robust M-Estimation regression estimates using Huber (1964) weight with c = 1.345. T-Statistics are provided in parentheses below the respective coefficients. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels

Industries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: CSSD												
HFSI	2.00***	2.68**	1.63***	2.39***	1.84***	1.09*	0.42	2.25***	0.91*	2.29***	2.85***	0.89***
β^{Stress}	(3.18)	(2.17)	(3.29)	(3.54)	(3.06)	(1.69)	(1.05)	(3.22)	(1.89)	(3.73)	(4.50)	(3.09)
LFSI	*-0.33*	**-1.08****	**-0.72*****	*0.05*	**-0.71*****	**-1.77*****	**-0.99*****	**-0.66***	**-0.91*****	**-0.93*****	**-1.03*****	**-0.32***
β^{Calm}	*(-1.40)*	**(-2.51)**	**(-3.43)**	*(0.06)*	**(-3.51)**	**(-6.67)**	**(-3.49)**	**(-1.71)**	**(-2.81)**	**(-2.90)**	**(-3.75)**	**(-1.69)**
cons	2.12***	3.13***	1.58***	3.13***	1.96***	2.98***	2.41***	3.13***	2.08***	2.49***	2.04***	1.41***
	(17.46)	(19.84)	(20.57)	(18.31)	(17.13)	(16.92)	(18.72)	(17.68)	(20.64)	(18.52)	(18.31)	(19.72)
R^2	0.0780	0.0684	0.1199	0.0591	0.0801	0.0338	0.0161	0.0556	0.0401	0.0946	0.1711	0.0538
adj. R^2	0.0718	0.0621	0.1140	0.0527	0.0739	0.0273	0.0095	0.0492	0.0336	0.0885	0.1655	0.0475
Panel B: CSAD												
HFSI	2.00***	2.69**	1.63***	2.40***	1.84***	1.09*	0.42	2.26***	0.91*	2.30***	2.85***	0.89***
β^{Stress}	(3.19)	(2.17)	(3.29)	(3.54)	(3.06)	(1.69)	(1.05)	(3.22)	(1.89)	(3.73)	(4.50)	(3.09)
LFSI	*-0.32*	**-1.08****	**-0.72*****	*0.05*	**-0.71*****	**-1.77*****	**-0.99*****	**-0.66***	**-0.91*****	**-0.93*****	**-1.03*****	**-0.32***
β^{Calm}	*(-1.40)*	**(-2.49)**	**(-3.42)**	*(0.06)*	**(-3.50)**	**(-6.67)**	**(-3.48)**	**(-1.71)**	**(-2.81)**	**(-2.90)**	**(-3.75)**	**(-1.69)**
cons	2.12***	3.15***	1.58***	3.14***	1.96***	2.98***	2.41***	3.14***	2.08***	2.50***	2.04***	1.41***
	(17.46)	(19.84)	(20.57)	(18.31)	(17.14)	(16.92)	(18.73)	(17.68)	(20.64)	(18.52)	(18.31)	(19.72)
N	300	300	300	300	300	300	300	300	300	300	300	300
R^2	0.0780	0.0684	0.1199	0.0591	0.0802	0.0338	0.0160	0.0556	0.0401	0.0946	0.1711	0.0538
adj. R^2	0.0718	0.0621	0.1140	0.0528	0.0740	0.0272	0.0094	0.0492	0.0336	0.0885	0.1655	0.0475

significant). For example, we find that for the Consumer Durables (2) and Utilities (8) industries, both β^{Calm} are -1.08 and -0.66 with t-statistics of -2.51 and -1.71 respectively. This evidence is consistent with the existence of individual stock return herding in nine out twelve industries, particularly in good or “calm” market conditions.

Overall, our findings are consistent with the evidence reported in Christie and Huang (1995) and suggest that for the industries considered and in our sample period, herding around the industry average is absent in stressful market conditions. Moreover, we document the herd behavior of individual stock returns around their industry average in relatively calm market conditions. Hwang and Salmon (2004) also reports evidence of herding in bear markets.

Herding and Extreme Returns

In the next section, we consider herd behavior of individual stock returns when the industry records unusually high or low returns. This inquiry is motivated by the findings of Barber and Odean (2007) who report evidence that individual investors are net buyers of attention-grabbing stocks, defined as those experiencing extreme one-day returns or abnormally high trading volume. Moreover, Bali, Cakici and Whitelaw (2011) find that investors exhibit a preference for stocks with extreme positive returns. Put together, these studies suggest that investors are attracted by extreme events, which we define, following prior research, as extreme one-day returns, positive or negative.

To identify those months with extreme events, we follow Bali, Cakici and Whitelaw (2011) and identify for each stock in our sample both maximum and minimum daily returns. We then compute each month and for each industry, an industry’s average maximum (minimum) daily return. Next, for each industry, we independently sort our sample based on the maximum (minimum) daily returns and form decile portfolios on this basis. Finally, we assign an indicator variable to months in the top and bottom decile portfolios formed based on the industry’s average maximum and minimum daily returns. We emphasize the independent sort between maximum and minimum daily returns because a stock’s month daily minimum return will not always rank in the lowest decile formed on the given stock’s maximum daily return. Therefore, MAX is an indicator variable for months in the highest decile of months ranked based on the industry’s average maximum daily return, and MIN is an indicator variable for months in the lowest decile of months ranked based on the industry’s average minimum daily return.

Finally, we estimate the following models:

$$CSSD_{j,t} = \alpha + \beta^{High} MAX_{j,t} + \beta^{Low} MIN_{j,t} + \varepsilon_{j,t} \qquad (7)$$

$$CSAD_{j,t} = \alpha + \beta^{High} MAX_{j,t} + \beta^{Low} MIN_{j,t} + e_{j,t} \qquad (8)$$

where CSSD and CSAD are defined and computed as described earlier. $MAX_{j,t}$ is an indicator variable that takes the value of one for months in the highest decile of months ranked based on the average industry (j) maximum daily return, and zero otherwise. $MIN_{j,t}$ is an indicator variable that takes the value of one for months in the lowest decile of months ranked based on the average industry minimum daily return, and zero otherwise.

We report the results of this exercise in Table 4. In Panel A of Table 4, we find that for nine out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly increases in months in which the industry’s average

Table 4. Extreme Returns and Herding

This table reports regression estimates for each industry of equations (3) and (4) over the entire sample period: January 1990 to December 2014. In Panel A. CSSD is defined as earlier and used as dependent variable. In Panel B, CSAD is defined as earlier and used as dependent variable. MAX is an indicator variable for months in the highest decile of months ranked based on the industry's average maximum daily return (MAXRET). MIN is an indicator variable for months in the lowest decile of months ranked based on the industry's average minimum daily return (MINRET). We report robust M-Estimation regression estimates using Huber (1964) weight with c = 1.345. T-Statistics are provided in parentheses below the respective coefficients. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels

Industries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: CSSD												
MAX	1.11**	1.47**	2.10***	0.13	2.74***	2.82***	0.73	2.27***	0.57	1.79***	1.94***	0.56**
	(2.03)	(2.11)	(4.87)	(0.21)	(4.38)	(3.33)	(1.38)	(3.09)	(1.42)	(2.94)	(3.35)	(2.01)
MIN	**-0.67*** **	**-0.73***	*-0.23*	*0.14*	**-0.45***	**-1.42*** **	**-0.82*** **	**-0.83** **	**-0.56** **	**-0.90*** **	**-0.54** **	**-0.38** **
	(-2.99)	**(-1.80)**	*(-1.06)*	*(0.30)*	**(-1.65)**	**(-5.08)**	**(-3.45)**	**(-1.98)**	**(-2.39)**	**(-3.77)**	**(-2.42)**	**(-2.31)**
cons	2.25***	3.27***	1.52***	3.34***	1.87***	2.85***	2.41***	3.17***	2.12***	2.58***	2.13***	1.46***
	(16.52)	(15.47)	(19.30)	(17.66)	(17.75)	(17.82)	(18.94)	(17.69)	(18.99)	(17.86)	(16.46)	(19.21)
R^2	0.0360	0.0254	0.1840	0.0004	0.1732	0.1210	0.0294	0.0655	0.0213	0.0716	0.0837	0.0318
adj. R^2	0.0295	0.0188	0.1785	-0.0064	0.1676	0.1151	0.0229	0.0592	0.0147	0.0653	0.0776	0.0253
Panel B: CSAD												
MAX	1.11**	1.48**	2.10***	0.13	2.75***	2.82***	0.73	2.28***	0.57	1.79***	1.94***	0.56**
	(2.03)	(2.11)	(4.87)	(0.21)	(4.38)	(3.33)	(1.38)	(3.09)	(1.42)	(2.94)	(3.35)	(2.01)
MIN	**-0.67*** **	**-0.73***	*-0.23*	*0.14*	*-0.45*	**-1.42*** **	**-0.82*** **	**-0.84** **	**-0.56** **	**-0.90*** **	**-0.54** **	**-0.38** **
	(-2.98)	**(-1.79)**	*(-1.06)*	*(0.30)*	*(-1.65)*	**(-5.08)**	**(-3.45)**	**(-1.97)**	**(-2.38)**	**(-3.76)**	**(-2.42)**	**(-2.31)**
cons	2.25***	3.28***	1.52***	3.34***	1.88***	2.85***	2.41***	3.18***	2.13***	2.58***	2.13***	1.46***
	(16.52)	(15.47)	(19.30)	(17.66)	(17.76)	(17.82)	(18.95)	(17.69)	(19.00)	(17.86)	(16.46)	(19.21)
N	300	300	300	300	300	300	300	300	300	300	300	300
R^2	0.0359	0.0253	0.1840	0.0004	0.1732	0.1210	0.0294	0.0655	0.0212	0.0716	0.0837	0.0318
adj. R^2	0.0294	0.0188	0.1785	-0.0064	0.1676	0.1151	0.0228	0.0592	0.0146	0.0653	0.0776	0.0253

Table 5. Good News, Bad News and Herding

This table reports regression estimates for each industry of equations (3) and (4) over the entire sample period: January 1990 to December 2014. In Panel A. CSSD is defined as earlier and used as dependent variable. In Panel B, CSAD is defined as earlier and used as dependent variable. HGH is an indicator variable for months in the highest decile of months ranked based on the industry's average GH ratio (IGH). LGH is an indicator variable for months in the lowest decile of months ranked based on the industry's average GH ratio (IGH). We report robust M-Estimation regression estimates using Huber (1964) weight with c = 1.345. T-Statistics are provided in parentheses below the respective coefficients. The symbols ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10 levels

Panel A: CSSD												
Industries	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HGH	*-0.26*	*-0.60*	**-0.47****	*0.47*	**-0.70*****	**-1.40*****	*-0.39*	**-1.27*****	**-0.64*****	**-0.58****	*-0.36*	**-0.46*****
	(-0.87)	*(-1.30)*	**(-2.17)**	*(0.72)*	**(-2.91)**	**(-5.26)**	*(-1.37)*	**(-3.30)**	**(-2.86)**	**(-2.05)**	*(-1.51)*	**(-3.03)**
LGH	0.67	2.65**	0.88**	1.64***	1.34***	3.50***	1.63***	0.49	1.04**	1.88***	2.44***	0.98***
	(1.30)	(2.42)	(2.20)	(2.81)	(2.72)	(4.36)	(2.71)	(0.89)	(2.34)	(2.75)	(3.94)	(3.88)
cons	2.25***	3.13***	1.66***	3.15***	2.03***	2.78***	2.27***	3.39***	2.08***	2.54***	2.06***	1.43***
	(16.30)	(18.18)	(18.22)	(17.58)	(15.89)	(17.71)	(19.47)	(17.27)	(19.43)	(18.38)	(16.88)	(18.93)
R^2	0.0108	0.0671	0.0436	0.0293	0.0543	0.1713	0.0649	0.0207	0.0493	0.0672	0.1224	0.0806
adj. R^2	0.0041	0.0608	0.0372	0.0228	0.0479	0.1657	0.0586	0.0141	0.0429	0.0609	0.1165	0.0745
Panel B: CSAD												
HGH	*-0.26*	*-0.60*	**-0.47****	*0.47*	**-0.70*****	**-1.40*****	*-0.39*	**-1.27*****	**-0.64*****	**-0.58****	*-0.36*	**-0.46*****
	(-0.86)	*(-1.29)*	**(-2.17)**	*(0.72)*	**(-2.92)**	**(-5.25)**	*(-1.37)*	**(-3.30)**	**(-2.86)**	**(-2.05)**	*(-1.51)*	**(-3.02)**
LGH	0.67	2.66**	0.88**	1.65***	1.35***	3.50***	1.63***	0.49	1.04**	1.88***	2.44***	0.98***
	(1.30)	(2.42)	(2.20)	(2.81)	(2.72)	(4.36)	(2.71)	(0.89)	(2.34)	(2.75)	(3.94)	(3.88)
cons	2.26***	3.15***	1.66***	3.16***	2.04***	2.78***	2.28***	3.40***	2.09***	2.54***	2.06***	1.43***
	(16.31)	(18.18)	(18.22)	(17.58)	(15.89)	(17.71)	(19.48)	(17.27)	(19.43)	(18.38)	(16.88)	(18.93)
N	300	300	300	300	300	300	300	300	300	300	300	300
R^2	0.0108	0.0671	0.0436	0.0293	0.0543	0.1712	0.0649	0.0207	0.0493	0.0672	0.1224	0.0806
adj. R^2	0.0041	0.0609	0.0372	0.0228	0.0479	0.1657	0.0586	0.0141	0.0429	0.0609	0.1165	0.0744

maximum daily return is at its highest (coefficients for β^{High} are positive and statistically significant). This finding suggests that there is no evidence of individual stock return herding in months in which the average firm in the industry attracts attention based on extreme positive returns. However, we also find that for ten out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly decreases in months in which the industry's average minimum daily return is at its highest (coefficients for β^{Low} are negative and statistically significant). For example, we find that for the Consumer Non-Durables (1) and Health Care (10) industries, both β^{Low} are -0.67 and -0.90 with t-statistics of -2.99 and -3.77 respectively. This evidence is consistent with the existence of individual stock return herding in ten out of twelve industries, in months where the average firm in the industry attracts attention based on extreme negative returns. Finally, using CSAD as the dependent variable (as reported in Panel B of Table 4), we find results quantitatively and qualitatively similar to those reported in Panel A.

Good News, Bad News and Herding

The evidence reported in Table 4 suggests that individual stock return herding around the industry average is concentrated in months in which firms in the various industries attract attention for earning extreme negative returns. Motivated by this finding, we investigate the herd behavior of individual stock returns around their industry average in months in which the industry received good or bad news. George and Hwang (2004) argue that stocks whose current prices are near (far) from their fifty-two-week high are those for which good (bad) news recently reached the market. To proxy for the arrival of industry wide good or bad news, we compute each industry's GH ratio (IGH) as the average of the individual stock distance to their respective fifty-two-week high prices. See equation (4).

Next, for each industry, we sort our sample based on the industry's average GH ratio and assign indicator variables to months in the top (HGH) and bottom (LGH). Therefore, HGH is an indicator variable for months in the highest decile of months ranked based on the industry's average GH ratio, identifying the months for which the given industry received good news. Similarly, LGH is an indicator variable for months in the lowest decile of months ranked based on the industry's average GH ratio, identifying the months for which the given industry received bad news. Finally, we estimate the following models:

$$CSSD_{j,t} = \alpha + \beta^{High} HGH_{j,t} + \beta^{Low} LGH_{j,t} + \varepsilon_{j,t} \tag{9}$$

$$CSAD_{j,t} = \alpha + \beta^{High} HGH_{j,t} + \beta^{Low} LGH_{j,t} + e_{j,t} \tag{10}$$

where CSSD and CSAD are defined and computed as described earlier. We report the results of this exercise in Table 5. Interestingly, we find in Panel A of Table 5 that for seven out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly decreases in months in which the industry's average GH ratio is at its highest (coefficients for β^{High} are negative and statistically significant). For example, we find that for the Manufacturing (3) and Retail (9) industries, both β^{Low} are -0.47 and -0.64 with t-statistics of -2.17 and -2.86 respectively. This finding suggests that for a majority of industries in our sample, there exists evidence of individual stock returns around the industry average when the industry receives good news. We also find that for ten out of the twelve industries considered, the cross-sectional standard deviation of returns around the industry average significantly increases in months in which the industries receive bad news or when the industry average GH ratio is at its lowest (β^{Low} are positive and statistically significant). These findings are qualitatively and quantitatively similar to those reported in Panel B of Table 5 where we employ the cross-sectional absolute deviation of returns as the dependent variable.

IV Conclusion

Recent evidence on the behavior of individual stock returns highlights the importance of herding in financial markets, particularly in stressful market conditions. In this paper, we revisit the notion that individual stock returns herd around their industry averages in stressful market conditions. Using the Volatility index (VIX) and the St. Louis Federal Reserve Financial Stress index (FSI) as measures market condition, we find evidence that herding appears to exist in months where VIX or FSI are at their lowest. In other words, individual stock returns herd around their industry average in calm, not stressful market conditions. In stressful markets, we find no evidence of individual stock return herding around their industry average. This finding is consistent with Christie and Huang (1995) and Chang, Cheng, and Khorana (2000) among others.

Building on the evidence of Barber and Odean (2007) who report that individual investors are net buyers of attention-grabbing stocks, defined as those experiencing extreme one-day returns and on Bali, Cakici and Whitelaw (2011) who find that investors exhibit a preference for stocks with extreme positive returns, we examine the herd behavior of individual stock returns in months when the industry attracts significant attention based on their recording of unusually high or low returns. We generally find that herding is concentrated in months in which the industries record the worst average daily returns (minimum daily returns), suggesting that herding is present in industries that attract attention for earning negative returns. Motivated by this latter finding, we build on the behavioral models of Hirshleifer, Subrahmanyam, and Titman (1994) and Banerjee (1992) among others to examine the herd behavior of individual stock returns in months where the industries receive good or bad news. Using the industry level average stock distance to the fifty-two-week high to capture the arrival of good or bad news as in George and Hwang (2004), we find that herding is concentrated in months where the industries receive good news and not bad news.

Overall, our study contributes to the literature in a few ways. First, we offer fresh evidence of the herd behavior of individual stock returns around their industry average in calm rather than stressful market conditions. Next, we document the herd behavior of individual stock returns in months in which the average firm in the industry records extreme negative rather than positive returns, and in months in which the average firm in the industry receives good rather than bad news. To the best of our knowledge, we are the first to document these latter findings. Ultimately, we offer new insight on the herd behavior of individual stock returns in financial markets. While we do not attempt to explain the apparent asymmetries documented in this study, we leave that for future research.

References

Bali, T., Cakici, N. and Whitelaw, N., 2011. “Maxing out: Stocks as lotteries and the cross-section of expected returns”. Journal of Financial Economics, vol. 99, no. 2 (February): 427-446.

Banerjee, A., 1992. A simple model of herd behavior, Quarterly Journal of Economics 107, 797-817.

Bebchuk, Lucian, and Yaniv Grinstein. 2005. "The Growth of Executive Pay." Oxford Review of Economic Policy, vol. 21, no. 2 (Summer):283-303.

Bikhchandani, S., D. Hirshleifer, and I. Welch, 1992, A theory of fads, fashions, customs, and cultural change as informational cascades, Journal of Political Economy 100, 992-1096.

Brennan, Michael J., Ashley W. Wang, and Yihong Xia. 2004 "Estimation and Test of a Simple Model of Intertemporal Capital Asset Pricing." Journal of Finance, vol. 59, no. 4 (August): 1743-1776.

Chan, Louis K.C., Josef Lakonishok and Bhaskaran Swaminathan, 2007. “Industry Classifications and Return Comovement”, Financial Analysts Journal, Vol. 63, No. 6, pp. 56-70

Chan, Wesley S., Richard Frankel, and S.P. Kothari. 2004. "Testing Behavioral Finance Theories Using Trends and Consistency in Financial Performance." Journal of Accounting and Economics, vol. 38 (December):3-50.

Chang, E. C., J. W. Cheng, and A. Khorana. 2000. “An Examination of Herd Behavior in Equity Markets: An International Perspective.” Journal of Banking and Finance 24: 1651–1679.

Chen, T. 2013. “Do Investors Herd in Global Stock Markets?” Journal of Behavioral Finance 14: 230–239.

Chiang, T. C., and D. Zheng. 2010. “An Empirical Analysis of Herd Behavior in Global Stock Markets.” Journal of Banking and Finance 34: 1911–1921.

Christie, W. G., & Huang, R. D. (1995). Following the pied piper: do individual returns herd around the market? Financial Analysts Journal, 51(4), 31-37.

Clarke, Richard N. 1989. "SICs as Delineators of Economic Markets." Journal of Business, vol. 62, no. 1 (January):17-31.

Daniel, Kent, and Sheridan Titman. 2006. "Market Reactions to Tangible and Intangible Information." Journal of Finance, vol. 61, no. 4 (August):1605-1643.

Demirer, R., A. M. Kutan, and C. D. Chen. 2010. “Do Investors Herd in Emerging Stock arkets?: Evidence from the Taiwanese Market.” Journal of Economic Behavior and Organization 76: 283–295.

Economic Classification Policy Committee. 1994. Report No. 1: Economic Concepts Incorporated in the Standard Industrial Classification Industries of the United States. Washington, DC: Bureau of Economic Analysis, U.S. Department of Commerce

Economou F., Hassapis C., and Philippas, N. 2018, “Investors’ fear and herding in the stock market.” Applied Economics, vol. 50, no. 34–35, 3654–3663

Economou, F., A. Kostakis, and N. Philippas. 2011. “Cross-Country Effects in Herding behavior: Evidence from Four South European Markets.” Journal of International Financial Markets, Institutions and Money 21: 443–460.

Economou, F., K. Gavriilidis, A. Goyal, and V. Kallinterakis. 2015. “Herding Dynamics in Exchange Groups: Evidence from Euronext.” Journal of International Financial Markets, Institutions and Money 34: 228–244.

Fama, Eugene F., and Kenneth R. French. 1997. "Industry Costs of Equity." Journal of Financial Economics, vol. 43, no. 2 (February):153-193.

Ferson, Wayne E., and Campbell R. Harvey. 1999. "Conditioning Variables and the Cross Section of Stock Retums." Journal of Finance, vol. 54, no. 4 (August):1325-1360.

Flannery, Mark J., and Kasturi P. Rangan. 2006. "Partial Adjustment toward Target Capital Structures." Journal of Financial Economics, vol. 79, no. 3 (March):469-506.

Francis, Jennifer, Ryan LaFond, Per Olsson, and Katherine Schipper. 2005. "The Market Pricing of Accruals Quality." Journal of Accounting and Economics, vol. 39, no.2 (June):295-327.

Galariotis, E. C., S. I. Krokida, and S. I. Spyrou. 2016. “Bond Market Investor Herding: Evidence from the European Financial Crisis.” International Review of Financial Analysis 48: 367–375.

George, T. and C. Hwang, 2004, The 52-Week High and Momentum Investing, Journal of Finance, 59, 2145-2176.

Gleason, K. C., C. I. Lee, and I. Mathur. 2003. “Herding Behavior in European Futures Markets.” Finance Letters 1: 5–8.

Gleason, K. C., I. Mathur, and M. A. Peterson. 2004. “Analysis of Intraday Herding Behaviour among the Sector ETFs.” Journal of Empirical Finance 11: 681–694.

Graham, John R., and Alok Kumar. 2006. "Do Dividend Clienteles Exist? Evidence on Dividend Preferences of Retail Investors." Journal of Finance, vol. 61, no. 3 (June):1305-1336.

Hasan, I., Tunaru, R., & Vioto, D. (2023). Herding behavior and systemic risk in global stock markets. Journal of Empirical Finance, 73, 107-133.

Hirshleifer, D., Subrahmanyam, A., & Titman, S. (1994). Security analysis and trading patterns when some investors receive information before others. *The Journal of Finance*, *49*(5), 1665-1698.

Hong, Harrison, Walter Torous, and Rossen Valkanov. 2007. "Do Industries Lead Stock Markets?" Journal of Financial Economics, vol. 83, no. 2 (February):367-396.

Hwang, S. and Salmon, M. 2004. “Market stress and herding”. Journal of Empirical Finance, vol. 11, no. 4 (September): 585-616

Hwang, S., and M. Salmon. 2004. “Market Stress and Herding.” Journal of Empirical Finance 11: 585–616.

Jiang, R., Wen, C., Zhang, R., & Cui, Y. (2022). Investor's herding behavior in Asian equity markets during COVID-19 period. Pacific-Basin Finance Journal, 73, 101771.

Kallinterakis, V., and T. Kratunova. 2007. “Does Thin Trading Impact upon the Measurement of Herding? Evidence from Bulgaria.” Ekonomia 10: 42–65.

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

Mobarek, A., S. Mollah, and K. Keasey. 2014. “A Cross-Country Analysis of Herd Behavior in Europe.” Journal of International Financial Markets Institutions and Money 32: 107–127.

Moskowitz, Tobias J., and Mark Grinblatt. 1999. "Do Industries Explain Momentum?" Journal of Finance, vol. 54, no. 4 (August): 1249-1290.

Newey, W., and K. West. 1987. “A Simple, Positive Semi- Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” Econometrica 55: 703–708.

Pastor, Lubos, and Robert F. Stambaugh. 1999. "Costs of Equity Capital and Model Mispricing." Journal of Finance, vol. 54, no. 1 (February):67-121.

Philippas, N. 2014. “Does Herd Behaviour Exist in the Commodities Market?” International Journal of Portfolio Analysis and Management 1: 330–344.

Philippas, N., F. Economou, V. Babalos, and A. Kostakis. 2013. “Herding Behavior in REITs: Novel Tests and the Role of Financial Crisis.” International Review of Financial Analysis 29: 166–174.

Pumanandam, Amiyatosh, and Bhaskaran Swaminathan. 2005. "Do Stock Prices React to SEO Announcements? Evidence from SEO Valuation." Working paper, Cornell University.

Richardson, Scott. 2006. "Over-Investment of Free Cash Flow." Review of Accounting Studies, vol. 11, no. 2-3 (June-September): 159-189.

Scharfstein, D. S., and J. C. Stein, 1990, Herd behavior and investment, American Economic Review 80, 465-479.
Sias, R. 2004. "Institutional Herding." Review of Financial Studies 17: 165–206.
Spyrou, S. 2013. "Herding in Financial Markets: A Review of the Literature." Review of Behavioral Finance 5: 175–194.
Tan, L., T. C. Chiang, J. R. Mason, and E. Nelling. 2008. "Herding Behavior in Chinese Stock Markets: An Examination of A and B Shares." Pacific-Basin Finance Journal 16: 61–77.
Trueman, B., 1994, Analyst forecasts and herding behavior, Review of Financial Studies 7, 97-124.
Wermers, R. 1999. "Mutual Fund Herding and the Impact on Stock Prices." Journal of Finance 54: 581–622.
Whaley, R. E. 2000. "The Investor Fear Gauge." The Journal of Portfolio Management 26: 12–17.
Whaley, R. E. 2009. "Understanding the VIX." Journal of Portfolio Management 35: 98–105.
Wulf, Julie. 2002. "Internal Capital Markets and Firm-Level Compensation Incentives for Division Managers." Journal of Labor Economics, vol. 20, no. 2, pt. 2 (April): S219-C262.