Article

The COVID-19 Pandemic and Herding Behaviour: Evidence from India's Stock Market

Millennial Asia
11(3) 366–390, 2020

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DOI: 10.1177/0976399620964635
journals.sagepub.com/home/mla

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Abstract

This article examines the herding behaviour at the industry level from national stock exchange (NSE). The novel contribution of this article is to examine the herding behaviour during the whole, pre- and post-coronavirus disease 2019 (COVID-19) pandemic outbreak period. We deployed the popular model proposed by Chang et al. (2000) to examine herd formation. Using daily stock closing prices of 191 firms, which constitute the 12 industry indices for the period from 1 January 2015 to 1 June 2020, the results for the full sample period (1 January 2015 to 1 June 2020) and before COVID-19 outbreak period (1 January 2015 to 29 January 2020) indicate the non-existence of herding formation at the industry level, but they do suggest a strong evidence of anti-herding behaviour. In addition, during the bull and bear market conditions, we found evidence of herding behaviour during the post-COVID-19 outbreak period (1 January 2020 to 1 June 2020). Further, the findings suggest that COVID-19 pandemic caused the formation of herding behaviour at the industry level. The study facilitates investors to devise their trading strategies in the regime of the COVID-19 pandemic.

Keywords

COVID-19, herding behaviour, industry, investor behaviour

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I. Introduction

In the finance literature, behavioural aspect in investment decision has always been a debatable topic for investors, financial asset managers as well as academic researchers (BenSaïda et al., 2015; Chauhan et al., 2019). Behavioural finance suggests that investors mimic others' action, especially during the turbulent period of fear, uncertainty and panic. The ongoing coronavirus disease 2019 (COVID-19) pandemic has wreaked havoc all over the world economies as well as weakened the stock markets' performance and has caused panic among stock market participants.

Since December 2019, an unprecedented disease that originated from the Republic of China and was later named as COVID-19 has spread across the world to become a pandemic. After the mass spread of the COVID-19 pandemic within the Republic of China, specifically in the province state of Wuhan, the negative effect of COVID-19 outbreak has been felt all over the world. On 30 January 2020, the World Health Organization (WHO) announced the COVID-19 pandemic as a Public Health Emergency of International Concern (PHEIC) to warn the countries over the world about the spread of the deadly virus. On 11 March 2020, the WHO declared COVID-19 as a pandemic. However, on 24 June 2020, India reported 4,56,183 confirmed positive cases of COVID-19, including 14,476 deaths, 1,83,022 active cases and 2,58,685 recoveries (*Indian Express*, 2020). The COVID-19 pandemic destabilized the global financial markets, including India's stock market.

In this article, we examine whether the COVID-19 outbreak causes herd formation in stock markets, specifically at the industry level. Researchers who focused on herd behaviour tend to agree that it is one of the common irrational investment behaviours that may cause abnormal losses and returns in a financial market (Bui et al., 2018). Banerjee (1992) defines herding as 'everybody doing what everyone else is doing even when their private information suggests doing something else'. Herding behaviour refers to the investor's tendency to mimic the behaviour of other investors. It is observed that during the turbulent period of uncertainty, investor follows the crowd decision with suppressing their private information (Chauhan et al., 2019). Herd formation causes asset prices to deviate from fundamental value, aggravate volatility of returns, destabilize financial markets, exacerbate the crises and eventually increase the fragility of the financial system (Javaira & Hassan, 2015).

A large number of studies have been conducted to detect investor herding behaviour in the past two decades. However, to the best of our knowledge, this study is the pioneering research work to examine the herding behaviour in the financial market under the present conditions of the COVID-19 pandemic. In normal circumstances, people would have sufficient time to collect adequate information, think rationally, analyse the market and make informed decisions (Mertzanis & Allam, 2018). However, in periods of market distress, for instance, the COVID-19 outbreak, investor is more inclined to follow the crowd decision with suppressing their private information. This article focuses on the Indian stock market and examines whether there is evidence of herding behaviour. Moreover,

we test for herding behaviour during both the pre- and post-COVID-19 outbreak phases as well as for the whole period.

We examine the herd behaviour from an industry perspective for two main reasons. First, this article follows the suggestions of Bikhchandani and Sharma (2001) and Bui et al. (2018), and they argue that investors generally face a similar investment decision problems and intend to observe the trades of others at the industry level. Additionally, asset managers' suggestions, financial analyst's analysis and investors' decisions are based on information dispersed at the industry level (Demirer et al., 2010). Second, the industry index is composed of different stocks, and it is a good approach where herd behaviour in the Indian stock market occurs at the industry level.

We examine the herding behaviour using the cross-sectional absolute deviation (CSAD) measure proposed by Chang et al. (2000). Our findings indicate non-existence of herding behaviour at industry level for full sample and pre-COVID-19 pandemic period, but they do suggest the strong evidence of anti-herding behaviour. In contrast, we found strong evidence of herding behaviour in bull market conditions during the post-COVID-19 outbreak, and also found some evidence of herding formation in bear market conditions. Moreover, our findings contribute to identification of potential risks and guides in devising an appropriate strategy for investment in stock markets during the regime of the COVID-19 pandemic. The rest of the article is organized as follows. Section II discusses the relevant literature. Section III provides the rationale of the study. Section IV explains the data and methodology. Section V presents a relevant methodology to detect herding behaviour. Section VI discusses and presents the empirical results of the study. Section VII concludes the article and provides practical implications for the stock market's participants.

II. Literature Review

Christie and Huang (1995) defined herding behaviour as an environment where group decisions are followed by investors. Previous studies documented that herding behaviour intensely affected the movement of the stock markets (Jaiyeoba et al., 2018; Ph & Uchil, 2019). Herding causes volatility in the stock markets that disturb the financial system, and therefore, it is an important factor for the policymakers who aim to stabilize the markets (Demirer & Kutan, 2006). Scharfstein and Stein (1990) argue that portfolio managers are more proven to herding behaviour because they are worried about losing their reputation. In the context of institutional and individual herding, Nofsinger and Sias (2002) documented that institutional investors do excessive positive feedback trading compared to individual investors. Besides, they found that institutional investors' herding influences asset returns to a great extent than individual investors' herding. The most cited study of Bikhchandani et al. (1992) argued that informational cascades facilitate to explain the localized conformity of behaviour and the fragility of mass behaviours, which implies an informational cascade occurs when it is optimal for an individual, having observed the actions of those ahead of him.

Chang et al. (2000) found significant prevalence of herding behaviour in South Korean and Taiwanese stock markets and do suggest partial evidence of herding behaviour in Japanese stock markets. In addition, they documented that the US and Hong Kong stock markets are free from herding behaviour. In context, in China, Tan et al. (2008) found that herding behaviour is more severe under up-market conditions, high trading volume and high volatility in Chinese A share market, while they found the absence of herding behaviour in B share market. Further, findings of Chiang and Zheng (2010) suggested that herding behaviour causes deviation in asset prices. Using the data of frontier stock markets, Balcilar et al. (2014) found strong evidence of herding behaviour in Dubai, Kuwait, Qatar and Saudi Arabian stock markets, while they do suggest weak herding behaviour in the Abu Dhabi stock market. During the crisis period, Asian markets are driven by herding behaviour, but American markets are free from herding formation (Chiang & Zheng, 2010). Lakonishok et al. (1992) documented that herding behaviour can be seen in the stock market securities, having a short time horizon. In the context of Italian stock market, Caparrelli et al. (2004) stated that herding behaviour is more common in extreme market conditions. Philippas et al. (2020) documented that the sentiment of investors is attached with different external signals, as they are received from different sources.

Furthermore, Lao and Singh (2011) found a significant presence of herding behaviour in Indian and Chinese stock markets and stated that it was more severe in the Chinese share market. In contrast, recent studies of Kumar et al. (2016) and Dutta et al. (2016) did not find significant presence of market-wise herding in the context of Indian stock market. In addition, Ganesh et al. (2016) examined the presence of herding behaviour at the industry level and found no sign of herding behaviour in the Indian stock market. Moreover, it is interesting to note that findings of recent studies support efficient market hypothesis (Fama, 1970)—this implied that Indian stock markets are informationally efficient, and investors are rational in the selection of financial assets. However, the ongoing COVID-19 pandemic has created an environment of panic and fear in stock markets that has resulted in high volatility, high market concentration, low returns and relatively high inability to mobilize new investment. Therefore, we suppose that probability of herd formation in the Indian stock market during the present conditions of the COVID-19 pandemic is relatively higher than in normal market conditions.

III. Rationale of the Study

Previous studies on pandemics, for instance, SARS, Ebola, Zika, and H1N1, or HIV/AIDS, provide empirical evidence of the impact of epidemics, associated risks and costs and mitigation strategies on the stock markets (Haacker, 2004; Hoffman & Silverberg, 2018; Liu et al., 2020; Loh, 2006; Pendell & Cho, 2013). The ongoing deadly COVID-19 outbreak has wreaked havoc on world economies as well as weakened the stock markets' performance and hurt the sentiments of stock market participants. India has been greatly hit by the COVID-19 pandemic (*Times of India*, 2020); hence, the COVID-19 pandemic has proved to be an

unprecedented shock. Stock markets have not yet demonstrated their safe haven properties during any major economic crisis and recession, and early evidence suggests that stock markets failed to display hedging opportunities and flight to safety properties during the COVID-19 pandemic (Albulescu, 2020; Liu et al., 2020; Zhang et al., 2020). Given this finding, we assume that the COVID-19 pandemic can have a black swan effect on the stock market, resulting in behavioural anomalies such as conditional and unconditional herding. Herding behaviour among investors can explain some of the behavioural anomalies against the efficient market hypothesis. However, to the best of authors' knowledge, it is the first attempt to uncover the herding behaviour in the regime of the COVID-19 pandemic. Furthermore, this study investigates the herding behaviour in different market conditions, for instance, bullish and bearish market conditions. This article attempts to present an integrated model to test the herding behaviour in the period of pandemic.

IV. Data and Methodology

Data

This study examines the herding behaviour using the daily closing prices of stocks that constituents the sectoral indices of NSE (see Table 1). The sectoral indices of NSE represent the whole industry-wise economy. Table 1 presents the details of the sample for the study, indicating industry index, industry name corresponding to industry index, the abbreviation of industry name used in the analysis and the number of companies that constitute the index corresponding to the industry. On 30 January 2020, the WHO announced the COVID-19 pandemic as a PHEIC to

Table 1. Sectoral Indices of NSE

Indices	Industry/Sector	Abbreviations	*N*
Nifty Auto Index	Automobile	AUTO	15
Nifty Bank	Banking	BANK	12
Nifty Financial Services Index	Financial services	FIN	20
Nifty FMCG Index	Fast-moving consumer goods	FMCG	15
Nifty IT Index	Information technology	IT	10
Nifty Media Index	Media and entertainment	MEDIA	14
Nifty Metal Index	Metal	METAL	15
Nifty Pharma Index	Pharmaceutical	PHARMA	10
Nifty Realty Index	Real estate	REALTY	10
Nifty Energy Index	Energy	ENERGY	10
Nifty Services Index	Services	SERVICES	30
Nifty Infra Index	Infrastructure	INFRA	30

Source: Compile from NSE website.
Notes: *N* represents the number of companies constitutes an index.

warn the countries about its spread over the world. Later, the WHO declared COVID-19 as a pandemic on 11 March 2020. To detect the herding behaviour among stock market participants pre and post the COVID-19 outbreak, we subdivided the full sample data according to the WHO timeline. Therefore, we decided the cut-off date to subdivide the full sample data into pre and post the COVID-19 outbreak for the study as 30 January 2020, when WHO declared COVID-19 as a PHEIC. Hence, the full sample data have been divided from 01 January 2015 to 01 June 2020 into three subsamples as follows:

1. Whole period: from 01 January 2015 to 01 June 2020
2. Pre-COVID-19 outbreak: from 01 January 2015 to 29 January 2020
3. Post-COVID-19 outbreak: from 30 January 2020 to 01 June 2020

In normal circumstances, people would have sufficient time to collect adequate information, think rationally, analyse the market and make informed decisions (Mertzanis & Allam, 2018). Therefore, we took more than 5 years of data before the COVID-19 pandemic to detect the herding behaviour, and we assumed that the market was in normal trading phase before the COVID-19 outbreak. We obtained all data sets from the ProwessIQ, powered by Centre for Monitoring of Indian Economy (CMIE) database. Further, the entire data set was analysed using Microsoft Excel and Stata.

Methodology

First, we drive the daily return of stock i on day t using the following equation:

$$R_{it} = \ln\left[\frac{P_{i,t}}{P_{i,t-1}}\right] \times 100 \tag{1}$$

where, $R_{i,t}$ is the stock return i on day t, ln is the natural logarithm, $P_{i,t}$ denotes the closing price for stock i on day t and $P_{i,t-1}$ is the closing price of stock i in the previous trading day, whereas the cross-sectional average stock of N returns ($R_{m,t}$) is calculated by taking an average of all individual stock returns on day t as per the following equation:

$$R_{m,t} = \frac{\Sigma R_{i,t}}{N} \tag{2}$$

where $R_{i,t}$ is the observed stock return of firm i at time t, and N is the number of firms included in the industry index.

V. Empirical Methods for Herding Detection

Literature has classified the school of thoughts to test the herding behaviour into broadly two categories—the first school of thought uses the trading data, including buy and sell orders executed by the participants in a given time period (Lakonishok et al., 1992), and the second school of thought uses the financial assets returns

organized into groups of similar characteristics like a country or industry classifications (Chang et al., 2000; Christie & Haung, 1995). Moreover, in this study, we follow the second school of thought to detect the herding behaviour at the industry level by examining the CSAD of stock returns in three phases, respectively—the whole period, pre-COVID-19 outbreak and post-COVID-19 outbreak. We test for herding behaviour at the industry level.

Chang et al.'s Method with Cross-sectional Absolute Deviation Measure

Previous studies suggest two widely used measures to detect herding behaviour. One model is proposed by Christie and Haung (1995) and the second by Chang et al. (2000). Literature suggests that issues with cross-sectional dispersion (CSSD) model of Christie and Haung (1995) are threefold. First, Economou et al. (2011) provided evidence that calculated CSSD can be easily biased by an outlier in the data series. Second, Hwang and Salmon (2004) noted that the deployment of dummies to capture extreme market conditions is rather crude, as it limits the sample upon which herding behaviour is tested, for instance, herding behaviour may exist in the stock markets during periods of mild market returns, and this is something the aforementioned model cannot identify (Erdenetsogt & Kallinterakis, 2016). Third, the aforementioned model proposes a linear relationship between CSSD of returns and absolute return of market during the prevalence of herding behaviour; however, there is little certainty of proposed relationship during the presence of herding behaviour. Findings of Lux (1995) and Lux and Marchesi (1999) provide evidence that herding behaviour is capable of introducing non-linear dynamics in the market. Therefore, to account for the aforementioned issues, we use the popular model proposed by Chang et al. (2000) to detect the herding behaviour. As a modification of the Christie and Huang (1995) method, Chang et al. (2000) propose another CSAD, an empirical method for the detection of herding towards average, which is statistically defined as follows:

$$\mathrm{CSAD}_t = 1/N\sum_{i=1}^{N} |R_{i,t} - R_{m,t}| \tag{3}$$

where CSAD_t is a proxy that indicates the distance from the market average return, how much of the stock returns are dispersed around the average return, N is the total number of stocks in industry index, $R_{i,t}$ is the return of stock i on day t and the variable $R_{m,t}$ is the cross-sectional average market return at day t. Since herding would increase the correlation of stock returns, the presence of herding in the market would transform the linear relationship between individual stock return and market return based on the capital asset pricing model into a non-linear relation (Mertzanis & Allam, 2018). Following the Lee et al. (2013) study, we examine the herding behaviour using the modified regression model as per the following equation:

$$\mathrm{CSAD}_t = \alpha + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R_{m,t}^2 + \varepsilon_t \tag{4}$$

where, $R_{m,t}$ is the cross-section average return of sample on day t and is used to account for asymmetric behaviour under different market conditions; $|R_{m,t}|$ is the absolute market return at day t, used to account for the magnitude and not the direction of the market; $R^2_{m,t}$ is the squared value of the equally weighted portfolio; $R_{m,t}$, captures the non-linear relationship that would arise because of the herding behaviour in the market. According to Chang et al. (2000), the presence of significantly negative non-linear coefficient γ_3 confirms the existence of herding behaviour; otherwise, a statistically positive γ_3 indicates no evidence of herding.

Previous studies documented that the rate of increase in dispersion with respect to aggregate market returns is higher in increasing trends compared to decreasing trends. We estimated regression coefficient separately for positive and negative market returns to investigate the asymmetry in bullish and bearish market conditions, specifically, using the following models:

$$\mathrm{CSAD}_t^{\mathrm{Up}} = \alpha + \gamma_1^{\mathrm{Up}} |R_{m,t}^{\mathrm{Up}}| + \gamma_2^{\mathrm{Up}} (R_{m,t}^{\mathrm{Up}})^2 + \varepsilon_t, \text{ if } R_{m,t} > 0 \quad (5)$$

$$\mathrm{CSAD}_t^{\mathrm{Down}} = \alpha + \gamma_1^{\mathrm{Down}} |R_{m,t}^{\mathrm{Down}}| + \gamma_2^{\mathrm{Down}} (R_{m,t}^{\mathrm{Down}})^2 + \varepsilon_t, \text{ if } R_{m,t} < 0 \quad (6)$$

where, $\mathrm{CSAD}_t^{\mathrm{Up}}$ ($\mathrm{CSAD}_t^{\mathrm{Down}}$) is the CSAD at day t corresponding to rising (declining) market returns, $R_{m,t}^{\mathrm{Up}}$ ($R_{m,t}^{\mathrm{Down}}$) represents equal-weighted portfolio returns during the bull (bear) market condition on day t and $(R_{m,t}^{\mathrm{Up}})^2$ $[(R_{m,t}^{\mathrm{Down}})^2]$ is the squared value of the equal-weighted portfolio to investigate the non-linearity in market returns when the market is rising (declining).

VI. Results

Descriptive Statistics

Table 2 provides descriptive statistics of CSAD_t of each industry for the whole sample data. To investigate the presence of herding behaviour in the stock market, we divided the whole data into three panels, that is, panel A presents the whole period, panel B presents before the COVID-19 outbreak period and panel C presents after the COVID-19 outbreak period. Panel A finds that the maximum value of CASD is found in media and realty industry, respectively, 1.641 and 1.611. Panel B reveals that values of CSAD corresponding to all industry are lower than in panel A. Results of panel C show that values of CSAD corresponding to all industry are marginally higher than in panels A and B.

Tables 3 and 4 provide descriptive statistics of CSAD_t of each industry in extreme market conditions, respectively, in bull and bear market conditions. More specifically, to investigate the presence of herding behaviour in upward trends and downward trends, further, we divided the whole data into three panels, that is, panel A presents the whole period, panel B presents before the COVID-19 outbreak period and panel C presents after the COVID-19 outbreak period. The normality test shows that all series of market return and CSAD are not normal since their skewness terms are different from 0, and their kurtosis coefficients

Table 2. Descriptive Statistics for Daily CSAD

	Panel A: Whole Period					Panel B: Pre COVID-19					Panel C: Post COVID-19				
Indices	Mean	St. Dev	Ske	Kurt	Obs.	Mean	St. Dev	Ske	Kurt	Obs.	Mean	St. Dev	Ske	Kurt	Obs.
AUTO	1.174	0.481	2.278	12.064	1336	1.119	0.381	0.976	1.580	1254	2.008	0.903	1.495	3.990	82
BANK	1.187	0.742	5.440	60.698	1336	1.115	0.603	6.861	117.177	1254	2.291	1.466	2.007	5.110	82
FIN	1.335	0.596	3.147	18.486	1336	1.270	0.454	2.061	10.990	1254	2.338	1.251	1.494	3.012	82
FMCG	1.120	0.409	1.346	3.067	1336	1.083	0.361	1.032	1.928	1254	1.678	0.637	0.525	0.217	82
IT	1.247	0.597	1.788	5.297	1336	1.200	0.533	1.521	3.841	1254	1.972	0.953	1.140	1.397	82
MEDIA	1.641	0.725	2.142	9.929	1336	1.582	0.653	2.216	13.212	1254	2.542	1.094	0.873	0.581	82
METAL	1.409	0.527	1.708	5.897	1336	1.365	0.465	1.204	2.991	1254	2.073	0.872	1.356	1.966	82
PHARMA	1.187	0.573	2.449	10.511	1336	1.138	0.487	1.983	8.442	1254	1.936	1.061	1.384	1.664	82
REALTY	1.611	0.712	2.132	9.520	1336	1.560	0.638	1.971	10.058	1254	2.405	1.177	1.225	2.090	82
ENERGY	1.224	0.602	3.122	19.949	1336	1.180	0.524	2.896	23.221	1254	1.903	1.112	1.881	3.750	82
SERVICES	1.258	0.556	3.697	23.342	1336	1.185	0.383	2.182	11.073	1254	2.375	1.217	1.526	2.981	82
INFRA	1.241	0.421	2.616	13.225	1336	1.197	0.342	1.970	11.446	1254	1.918	0.788	1.402	1.944	82

Source: The author.

Notes: This table reports the mean, standard deviation, skewness, kurtosis and observations of the cross-sectional absolute deviation (CSAD) over the sample period for all industries.

Table 3. Descriptive Statistics for Daily CSAD in Bull Market Conditions

	Panel A: Whole Period					Panel B: Pre-COVID-19					Panel C: Post COVID-19				
Indices	Mean	St. Dev	Ske.	Kurt.	Obs.	Mean	St. Dev	Ske	Kurt	Obs.	Mean	St. Dev	Ske	Kurt	Obs.
AUTO	1.191	0.476	2.021	9.203	694	1.141	0.386	0.952	1.636	655	2.037	0.890	1.180	2.652	39
BANK	1.202	0.811	6.564	76.719	678	1.134	0.685	8.459	135.533	640	2.346	1.584	2.281	7.126	38
FIN	1.344	0.560	2.404	10.519	707	1.289	0.468	2.224	12.780	667	2.264	1.012	0.759	0.326	40
FMCG	1.140	0.426	1.320	3.011	718	1.104	0.376	0.981	1.588	679	1.774	0.674	0.465	0.016	39
IT	1.243	0.582	1.465	3.135	701	1.201	0.528	1.354	3.131	658	1.890	0.901	0.536	0.625	43
MEDIA	1.693	0.726	1.502	3.384	703	1.636	0.659	1.362	2.988	666	2.715	1.060	0.734	0.089	37
METAL	1.445	0.526	1.690	6.373	695	1.407	0.475	1.154	2.625	653	2.045	0.839	1.997	4.882	42
PHARMA	1.196	0.564	2.402	9.950	692	1.129	0.436	1.274	2.617	644	2.090	1.098	1.136	0.786	48
REALTY	1.658	0.709	1.656	5.443	707	1.610	0.660	1.625	6.223	669	2.506	0.977	1.039	0.464	38
ENERGY	1.217	0.555	1.797	5.173	713	1.183	0.512	1.653	4.699	674	1.799	0.875	1.190	1.142	39
SERVICES	1.243	0.536	3.112	14.405	725	1.176	0.390	2.483	13.680	686	2.425	1.102	0.797	0.136	39
INFRA	1.228	0.405	2.110	9.174	729	1.185	0.335	1.316	3.971	690	2.000	0.679	1.730	3.307	39

Source: The author.

Notes: This table reports the mean, standard deviation, skewness, kurtosis and observations of the cross-sectional absolute deviation (CSAD) over the sample period for all industries.

Table 4. Descriptive Statistics for Daily CSAD in Bear Market Conditions

	Panel A: Whole Period					Panel B: Pre COVID-19					Panel C: Post COVID-19				
Indices	Mean	St. Dev	Ske	Kurt	Obs.	Mean	St. Dev	Ske	Kurt	Obs.	Mean	St. Dev	Ske	Kurt	Obs.
AUTO	1.155	0.485	2.560	15.205	642	1.095	0.374	1.006	1.537	599	1.981	0.925	1.808	5.703	43
BANK	1.172	0.664	3.100	16.284	658	1.095	0.503	1.802	6.090	614	2.243	1.372	1.675	2.494	44
FIN	1.325	0.633	3.713	23.708	629	1.248	0.438	1.829	8.271	587	2.408	1.452	1.613	2.835	42
FMCG	1.096	0.388	1.356	3.022	618	1.059	0.341	1.076	2.401	575	1.590	0.596	0.530	–0.631	43
IT	1.252	0.613	2.090	7.206	635	1.199	0.538	1.700	4.610	596	2.063	1.010	1.615	2.580	39
MEDIA	1.583	0.721	2.911	18.218	633	1.520	0.641	3.313	27.444	588	2.400	1.112	1.083	1.378	45
METAL	1.370	0.526	1.758	5.582	641	1.321	0.450	1.270	3.569	601	2.102	0.915	0.863	0.185	40
PHARMA	1.178	0.582	2.503	11.134	644	1.148	0.537	2.320	10.361	610	1.717	0.980	1.964	4.831	34
REALTY	1.559	0.712	2.702	14.644	629	1.502	0.606	2.475	16.621	585	2.317	1.331	1.376	2.504	44
ENERGY	1.233	0.652	4.002	27.890	623	1.176	0.537	4.146	41.077	580	1.997	1.293	1.903	3.158	43
SERVICES	1.275	0.579	4.238	30.908	611	1.195	0.373	1.781	7.510	568	2.331	1.325	1.956	4.632	43
INFRA	1.257	0.439	3.080	16.524	607	1.213	0.350	2.679	19.084	564	1.844	0.875	1.392	1.632	43

Source: The author.

Notes: This table reports the mean, standard deviation, skewness, kurtosis and observations of the cross-sectional absolute deviation (CSAD) over the sample period for all industries.

largely exceed 3 (BenSaïda et al., 2015). Moreover, the $CSAD_t$ series are stationary but non-normal and asymmetrical, since their kurtosis largely exceeds the threshold. Further, the Jarque–Bera test statistics were found significant for both $CSAD_t$ and $R_{m,t}$ in different markets phases. Further, we employed the Jarque–Bera test, and its results suggest the rejection of the null hypothesis of a normal distribution of $CSAD_t$ and $R_{m,t}$ time series.

Herding Behaviour in the Indian Stock Market

Table 5 provides the regression results for all industries as per Equation (4). Panel A of Table 5 provides the results for the full sample period corresponding to all industries. Except for AUTO, FMCG and IT, the estimated coefficient γ_3 in other industries is statistically significantly positive, indicating that investors intend to anti-herd behaviour in these industries. However, γ_3 is positive and statistically significant, indicating no evidence of herding behaviour because industry

Table 5. Estimating Regression Coefficients of the Daily $CSAD_t$ on Equation (4)

Indices	α	γ_1	γ_2	γ_3	*F*-stat	Adj. R^2
Panel A: Whole period from 01/01/2015 to 01/06/2020						
AUTO	0.923	0.029	0.263	−0.003	178.25***	0.285
	(51.946)***	(3.685)***	(14.660)***	(−1.275)		
BANK	0.802	0.073	0.327	0.005	262.297***	0.370
	(31.469)***	(7.276)***	(15.372)***	(2.200)*		
FIN	1.042	0.023	0.286	0.004	263.764***	0.371
	(53.617)***	(2.491)*	(16.184)***	(2.079)*		
FMCG	0.904	0.053	0.307	−0.007	155.823***	0.258
	(57.045)***	(5.488)***	(14.213)***	(−1.927)		
IT	0.973	0.008	0.318	−0.006	123.838***	0.216
	(41.230)***	(0.666)	(11.975)***	(−1.576)		
MEDIA	1.249	0.080	0.357	0.007	166.915***	0.272
	(41.810)***	(6.369)***	(10.856)***	(1.195)		
METAL	1.108	0.040	0.226	0.009	246.272***	0.355
	(54.821)***	(5.608)***	(12.141)***	(3.014)**		
PHARMA	0.920	0.013	0.255	0.011	155.720***	0.258
	(39.722)***	(1.311)	(9.974)***	(2.550)*		
REALTY	1.316	0.070	0.202	0.030	218.544***	0.328
	(49.312)***	(6.453)***	(7.505)***	(6.923)***		
ENERGY	0.977	0.017	0.206	0.025	225.562***	0.335
	(42.695)***	(1.679)	(8.240)***	(6.606)***		
SERVICES	0.971	0.041	0.344	0.006	335.807***	0.429
	(55.645)***	(4.040)***	(17.237)***	(2.414)**		
INFRA	1.109	−0.033	0.119	0.012	76.308***	0.145
	(59.061)***	−(3.726)	(5.225)***	(2.744)**		

(Table 5 continued)

(Table 5 continued)

Indices	α	γ_1	γ_2	γ_3	*F*-stat	Adj. R^2
Panel B: Pre COVID-19 from 01/01/2015 to 29/01/2020						
AUTO	0.957	0.023	0.181	0.001	81.967***	0.162
	(56.183)***	(2.848)**	(8.439)***	(0.248)		
BANK	0.902	0.039	0.119	0.048	163.681***	0.280
	(34.293)***	(3.642)***	(3.839)***	(7.418)***		
FIN	1.077	0.015	0.198	0.014	98.532***	0.189
	(51.442)***	(1.541)	(6.658)***	(1.860)		
FMCG	0.934	0.054	0.188	0.028	101.568***	0.194
	(57.043)***	(5.093)***	(6.658)***	(3.236)**		
IT	0.995	0.014	0.228	0.016	73.196***	0.147
	(40.601)***	(1.061)	(6.494)***	(1.731)		
MEDIA	1.267	0.081	0.268	0.025	148.230***	0.261
	(44.904)***	(6.615)***	(8.101)***	(3.543)***		
METAL	1.130	0.036	0.163	0.022	166.263***	0.284
	(53.565)***	(4.847)***	(6.625)***	(4.021)***		
PHARMA	0.942	−0.008	0.180	0.022	87.479***	0.172
	(39.706)***	(−0.756)	(5.368)***	(2.495)*		
REALTY	1.327	0.074	0.126	0.050	180.848***	0.301
	(49.597)***	(6.853)***	(3.917)***	(7.408)***		
ENERGY	0.984	0.034	0.159	0.037	157.606***	0.273
	(45.087)***	(3.046)**	(6.226)***	(7.823)***		
SERVICES	1.015	0.008	0.226	0.015	96.306***	0.186
	(58.134)***	(0.758)	(7.568)***	(1.580)		
INFRA	1.089	−0.016	0.116	0.003	42.592***	0.091
	(67.481)***	(−1.738)	(5.850)***	(0.617)		
Panel C: Post COVID-19 from 30/01/2020 to 01/06/2020						
AUTO	1.279	0.035	0.388	−0.016	16.480***	0.364
	(9.103)***	(1.280)	(5.111)***	(−2.289)*		
BANK	1.334	0.123	0.330	0.003	20.842***	0.424
	(6.126)***	(3.366)**	(3.607)**	(0.476)		
FIN	1.533	0.036	0.274	0.003	22.656***	0.445
	(8.879)***	(1.135)	(3.828)***	(0.497)		
FMCG	1.251	0.056	0.334	−0.017	14.349***	0.331
	(12.266)***	(2.086)*	(3.999)***	(−1.729)		
IT	1.412	−0.010	0.315	−0.013	9.663***	0.243
	(8.486)***	(−0.322)	(2.860)**	(−1.131)		
MEDIA	1.749	0.067	0.562	−0.038	7.196***	0.187
	(8.000)***	(1.242)	(3.430)**	(−1.659)		
METAL	1.456	0.045	0.243	0.002	20.969***	0.425
	(10.669)***	(1.766)	(3.102)**	(0.241)		
PHARMA	1.286	0.047	0.345	−0.003	15.911***	0.356
	(7.706)***	(1.307)	(2.928)**	(−0.233)		

(Table 5 continued)

(Table 5 continued)

Indices	α	γ_1	γ_2	γ_3	*F*-stat	Adj. R^2
REALTY	2.021	0.054	0.069	0.030	13.665***	0.319
	(10.479)***	(1.068)	(0.574)	(2.337)*		
ENERGY	1.351	−0.016	0.198	0.015	17.099***	0.374
	(7.244)***	(−0.450)	(1.574)	(1.064)		
SERVICES	1.505	0.081	0.332	0.005	27.379***	0.494
	(8.930)***	(2.353)*	(3.895)***	(0.651)		
INFRA	1.624	−0.045	0.147	0.012	6.989***	0.182
	(10.203)***	(−1.626)	(0.888)	(0.445)		

Source: The authors.
Notes: *t*-Statistics are given in parentheses. ***, ** and * Indicate significance at 0.001, 0.01 and 0.05, respectively.

dispersion increases as the rate increases, thus showing efficiency in market rather than herding. Furthermore, our findings suggest that investor's trade away from the market consensus. As a result, there is no evidence of herding employing the benchmark model for the entire sample period for all sectors. Therefore, our results are consistent with findings of Ganesh et al. (2016) who found that Indian equity market is free from industry-wise herding. As many previous studies provide convincing theoretical arguments that emerging markets are known for weak access to accurate and timely information, investors can earn high returns if they compromise with the market and invest accordingly. Therefore, markets are more driven by herding behaviour. Hence, our results do not support these theoretical arguments.

Panel B shows the regression result of the pre-COVID-19 period for all industries. Results of panel B provided the positive coefficient γ_3 for all sectors that suggest the anti-herd behaviour in Indian stock markets. Moreover, results of panel B reveal that market participants traded the trading away from the market consensus before the COVID-19 outbreak. The value of adjusted *R*-square is in the range of 9–30 per cent, implying appropriateness of the model for all sectors. Similarly, results of panel B is in line with findings of Ganesh et al. (2016). Furthermore, findings of Kumar et al. (2016) and Dutta et al. (2016) also fail to provide significant evidence of herding behaviour in the Indian equity market.

We are more interested in investigating the industry-wide herd behaviour after the COVID-19 outbreak. Panel C provided the regression results of all industries post-COVID-19 outbreak in India. Estimated coefficient γ_3 is found negative and significant for AUTO industry, indicating that investors intend to herd behaviour in the auto industry. The Indian government has changed its focus from fuel-run automobile sector to electronic vehicle industry to protect and sustain the environment for the coming generations. As a result, the Indian automobile industry experienced low demand for vehicles. Further, outbreak of the COVID-19 pandemic, high interest rates, high fuel price and high inflation have resulted in contraction of demand for vehicles. Therefore, it seems the outbreak of COVID-19 causes sell-side herding behaviour in the automobile sector. Besides, the estimated coefficient of γ_3, for FMCG, IT, media and pharma industry, was found

to be negative but insignificant—this implied that there was no evidence of herding behaviour in respective industries. The results of panel C provided some significant evidence of herd behaviour in the Indian stock markets after the COVID-19 pandemic. For robustness of predictive models, the value of adjusted *R*-square is in the range of 18–49 per cent, implying appropriateness of the model for all sectors.

Industry Herding Behaviour Under Bull Market Conditions

This and the immediate succeeding sections provide the empirical results of whether industry herding shows different behaviours under different market trends. We divided the full sample into two subsamples using the industry index returns, respectively, positive and negative industry index returns. Previous studies provided that herding behaviour is asymmetric based on stock market returns. Investors were prone to herding behaviour during the bull market conditions (Lee et al., 2013; Tan et al., 2008).

Table 6 reports the results of herding behaviour during the bull market conditions (positive returns) as per Equation (5). Panel A of Table 6 provided regression results of herding behaviour for all industries for the full sample period during positive returns. *F*-test statistic gives significant results, indicating that all models corresponding to all sectors have an overall good fit. The explanatory

Table 6. Estimating Regression Coefficient in Bull Market Conditions on Equation (5)

Indices	α	γ_1^{Up}	γ_2^{Up}	*F*-stat	Adj. R^2
Panel A: Whole period from 01/01/2015 to 01/06/2020					
AUTO	0.944	0.260	0.003	147.548***	0.297
	(36.379)***	(8.332)***	(0.582)		
BANK	0.949	0.071	0.076	290.395***	0.461
	(22.793)***	(1.550)	(9.791)***		
FIN	1.083	0.236	0.021	149.104***	0.296
	(33.993)***	(5.854)***	(2.514)*		
FMCG	0.891	0.354	0.000	150.371***	0.294
	(37.153)***	(9.609)***	(−0.052)		
IT	0.929	0.391	−0.019	86.840***	0.197
	(26.488)***	(8.791)***	(−2.222)*		
MEDIA	1.324	0.311	0.042	123.002***	0.258
	(27.507)***	(4.273)***	(2.045)*		
METAL	1.213	0.107	0.045	195.170***	0.359
	(39.614)***	(2.978)**	(5.855)***		
PHARMA	0.909	0.295	0.004	105.867***	0.233
	(27.159)***	(7.269)***	(0.441)		
REALTY	1.326	0.257	0.034	127.989***	0.265
	(29.576)***	(4.214)***	(2.285)*		

(Table 6 continued)

(Table 6 continued)

Indices	α	γ_1^{Up}	γ_2^{Up}	*F*-stat	Adj. R^2
ENERGY	0.963	0.238	0.023	113.934***	0.241
	(28.400)***	(5.361)***	(2.334)*		
SERVICES	1.036	0.168	0.073	260.085***	0.417
	(38.483)***	(3.983)***	(7.269)***		
INFRA	1.075	0.154	0.003	66.011***	0.152
	(43.940)***	(5.404)***	(0.639)		
Panel B: Pre COVID-19 from 01/01/2015 to 29/01/2020					
AUTO	0.973	0.195	0.001	66.639***	0.167
	(41.200)***	(6.564)***	(0.158)		
BANK	0.934	0.065	0.072	182.161***	0.362
	(23.733)***	(1.429)	(8.588)***		
FIN	1.087	0.217	0.010	66.328***	0.164
	(34.951)***	(4.897)***	(0.850)		
FMCG	0.916	0.249	0.035	90.403***	0.209
	(36.056)***	(4.919)***	(1.736)		
IT	1.003	0.190	0.040	56.220***	0.144
	(25.730)***	(2.770)**	(1.727)		
MEDIA	1.301	0.300	0.037	109.715***	0.246
	(28.576)***	(4.180)***	(1.754)		
METAL	1.161	0.176	0.025	127.430***	0.279
	(37.802)***	(4.648)***	(2.732)**		
PHARMA	0.958	0.155	0.026	57.274***	0.149
	(29.362)***	(2.904)**	(1.526)		
REALTY	1.285	0.247	0.040	150.650***	0.309
	(31.072)***	(4.356)***	(2.907)**		
ENERGY	0.939	0.248	0.025	75.647***	0.182
	(25.477)***	(3.986)***	(1.182)		
SERVICES	1.051	0.105	0.071	86.186***	0.199
	(41.771)***	(2.225)*	(4.387)***		
INFRA	1.075	0.121	0.000	32.599***	0.084
	(50.185)***	(4.799)***	(−0.064)		
Panel C: Post COVID-19 from 30/01/2020 to 01/06/2020					
AUTO	1.034	0.641	−0.046	20.490***	0.506
	(4.872)***	(3.946)***	(−2.059)*		
BANK	1.813	−0.202	0.102	25.184***	0.567
	(4.643)***	(−0.704)	(2.716)*		
FIN	1.467	0.350	−0.002	12.591***	0.373
	(5.680)***	(1.872)	(−0.079)		
FMCG	1.221	0.439	−0.025	14.486***	0.415
	(7.495)***	(2.796)**	(−1.063)		
IT	0.978	0.741	−0.070	10.418***	0.310
	(4.138)***	(3.928)***	(−2.938)**		

(Table 6 continued)

(Table 6 continued)

Indices	α	γ_1^{Up}	γ_2^{Up}	*F*-stat	Adj. R^2
MEDIA	2.482	−0.075	0.092	3.112	0.105
	(6.040)***	(−0.177)	(1.020)		
METAL	1.874	−0.307	0.109	35.976***	0.630
	(12.408)***	(−2.301)*	(4.876)***		
PHARMA	1.237	0.664	−0.054	11.269***	0.304
	(5.382)***	(3.760)***	(−2.212)*		
REALTY	2.460	−0.033	0.025	0.239	-0.043
	(6.941)***	(−0.077)	(0.278)		
ENERGY	1.720	−0.234	0.078	13.329***	0.394
	(7.388)***	(−1.117)	(2.551)*		
SERVICES	1.762	0.105	0.060	15.942***	0.440
	(5.640)***	(0.421)	(1.480)		
INFRA	1.599	0.265	−0.016	4.358*	0.150
	(6.938)***	(1.239)	(−0.515)		

Source: The authors.
Notes: *t*-Statistics are given in parentheses. ***, ** and * Indicate significance at 0.001, 0.01 and 0.05, respectively.

power is more than 15 per cent for all models, implying appropriateness of the model for all industries. Panel A reports that γ_1^{Up} coefficients for the up-market returns are significant and positive for all industries, whereas γ_2^{Up} coefficients are significant and positive, except AUTO, PHARMA, INFRA, FMCG and Information Technology (IT) industry, hence implying the presence of anti-herding behaviour for the whole period data in respective industries. Furthermore, γ_2^{Up} coefficient for IT industry regression model was found to be negative and significant, indicating the presence of herding behaviour in the IT sector. Moreover, the results of the full sample period suggest that investors do not mimic the herding behaviour during bull market conditions. Therefore, our results are consistent with findings of Ganesh et al. (2016), Kumar et al. (2016) and Dutta et al. (2016) who deny the evidence of herding behaviour during bull market conditions in the Indian stock market.

Panel B of Table 6 reports the regression results of herding behaviour at the industry level before the COVID-19 outbreak period in positive returns. The results of panel B showed that γ_1^{Up} coefficients for the up-market returns are significantly positive for 11 of the 12 industries, whereas γ_2^{Up} coefficients are positive and insignificant for the 4 of the 12 sectors, except for BANK, METAL, REALTY and SERVICES industry. Estimated coefficients γ_2^{Up} of BANK, METAL, REALTY and SERVICES sectors are positive and significant, indicating the anti-herding behaviour in respective industries before the COVID-19 outbreak. *F*-test statistic gives significant results, indicating all models corresponding to all sectors have an overall good fit. The explanatory power of the OLS model corresponding to all sectors decrease in panel B as compared to the OLS model corresponding to all sectors in panel A. Our findings of panel B are consistent with findings of panel A, which denies the presence of herding behaviour during

bull market conditions and in line with results of Ganesh et al. (2016), Kumar et al. (2016) and Dutta et al. (2016). Furthermore, the results reveal that herding behaviour was not prevalent in the Indian stock market before the spread of COVID-19 virus across the world.

Panel C of Table 6 reports regression results of herding behaviour for all industries during the COVID-19 outbreak period in bull market conditions. Estimated coefficients γ_2^{Up} of AUTO, IT and PHARMA sectors are negative and significant, indicating that the investors intended to herding behaviour in these industries. The rationale of herding behaviour in the PHARMA industry is that the pharmaceutical industry is at the forefront battling against the COVID-19 pandemic. Indian pharmaceutical companies ensure the adequate supplies of medicines to its customers across the world despite the supply chain disruptions and the lockdown restrictions in various countries (*The Economic Times*, 2020). Businesses, in the post-coronavirus world, will undergo a transition, and the biggest gainer could be the IT industry. Businesses, mainly those in the services sector such as banking and other financial services, education, retail, healthcare, food and grocery delivery will further embrace technology and automation to better leverage growth. Therefore, the COVID-19 pandemic ignites investment appeals to investors in the pharmaceutical and IT companies. Furthermore, estimated coefficients γ_2^{Up} of FIN, FMCG and INFRA sectors are negative but not significant. Additionally, estimated coefficients γ_2^{Up} of BANK, METAL and ENERGY industries are positive and significant, indicating that the investors intended to anti-herding behaviour in these industries. The results of panel C suggest that the COVID-19 outbreak leads to the herding behaviour in bull market conditions, specifically in automobile, IT and pharmaceutical industries.

Industry Herding Behaviour Under Bear Market Conditions

Table 7 presents the results of herding behaviour during the bear market conditions (negative returns) as per Equation (6). Panel A of Table 7 reports the regression results of herding behaviour for all industries, using the full sample period in negative returns. The estimated coefficient γ_2^{Down} of the regression model for AUTO, FMCG, IT, MEDIA and SERVICES was found to be negative and insignificant, suggesting that herding behaviour is not found in these sectors during the whole period sample. On the other side, findings of panel A reveal that estimated coefficient γ_2^{Down} is significantly positive for the REALTY, ENERGY and INFRA sectors' herding behaviour regression model, indicating the anti-herd behaviour in these sectors.

Panel B of Table 7 presents the results of the regression model industry-wise before the COVID-19 outbreak in India in bull market conditions. The estimated coefficient γ_2^{Down} of the regression model is positive and significant for FMCG, MEDIA, METAL, REALTY and ENERGY industry, implying anti-herding behaviour in these industries before the COVID-19 pandemic. Additionally, the estimated coefficient γ_2^{Down} of the regression model for BANK and SERVICES industries was found to be negative but statistically insignificant, indicating

Table 7. Estimating Regression, Coefficient in Bear Market Conditions on Equation (6)

Indices	α	γ_1^{Down}	γ_2^{Down}	*F*-stat	Adj. R^2
Panel A: Whole period from 01/01/2015 to 01/06/2020					
AUTO	0.911	0.247	–0.005	119.856***	0.271
	(35.327)***	(10.183)***	(–1.677)		
BANK	0.847	0.268	0.001	180.948***	0.354
	(26.195)***	(10.546)***	(0.297)		
FIN	1.035	0.273	0.003	248.282***	0.441
	(37.939)***	(11.677)***	(1.460)		
FMCG	0.926	0.243	–0.007	80.958***	0.206
	(42.292)***	(8.537)***	(–1.754)		
IT	1.000	0.279	–0.002	100.163***	0.238
	(30.059)***	(7.794)***	(–0.520)		
MEDIA	1.209	0.316	0.002	125.077***	0.282
	(28.747)***	(7.497)***	(0.285)		
METAL	1.057	0.237	0.002	190.406***	0.372
	(37.201)***	(9.758)***	(0.554)		
PHARMA	0.923	0.230	0.013	127.986***	0.283
	(28.096)***	(6.668)***	(2.642)**		
REALTY	1.311	0.136	0.029	203.306***	0.392
	(36.531)***	(4.069)***	(6.583)***		
ENERGY	0.991	0.178	0.026	219.770***	0.413
	(29.824)***	(5.224)***	(6.010)***		
SERVICES	1.001	0.304	0.004	287.056***	0.484
	(40.201)***	(11.554)***	(1.443)		
INFRA	1.177	0.007	0.048	51.384***	0.143
	(39.340)***	(0.159)	(4.690)***		
Panel B: Pre COVID-19 from 01/01/2015 to 29/01/2020					
AUTO	0.940	0.166	0.002	54.183***	0.151
	(38.100)***	(5.257)***	(0.274)		
BANK	0.833	0.270	–0.009	69.013***	0.182
	(24.524)***	(6.302)***	(–0.917)		
FIN	1.065	0.179	0.018	83.051***	0.219
	(38.197)***	(4.524)***	(1.829)		
FMCG	0.957	0.114	0.029	58.967***	0.168
	(43.548)***	(3.170)**	(3.088)**		
IT	1.007	0.215	0.013	54.486***	0.152
	(29.713)***	(4.724)***	(1.261)		
MEDIA	1.243	0.208	0.022	106.749***	0.265
	(31.489)***	(4.980)***	(2.924)**		
METAL	1.097	0.150	0.020	115.843***	0.277
	(37.653)***	(4.630)***	(2.862)**		
PHARMA	0.928	0.202	0.020	70.557***	0.186
	(25.767)***	(4.242)***	(1.804)		

(Table 7 continued)

(Table 7 continued)

Indices	α	γ_1^{Down}	γ_2^{Down}	*F*-stat	Adj. R^2
REALTY	1.362 (37.603)***	0.020 (0.505)	0.054 (7.163)***	114.095***	0.279
ENERGY	1.023 (34.358)***	0.092 (2.813)**	0.040 (8.280)***	171.954***	0.371
SERVICES	1.001 (41.151)***	0.286 (7.366)***	–0.013 (–1.167)	69.702***	0.195
INFRA	1.116 (43.790)***	0.082 (2.250)*	0.016 (1.666)	31.204***	0.097
Panel C: Post COVID-19 from 30/01/2020 to 01/06/2020					
AUTO	1.365 (6.481)***	0.308 (2.883)**	–0.013 (–1.506)	8.175**	0.255
BANK	1.536 (5.227)***	0.175 (1.542)	0.003 (0.507)	13.448***	0.367
FIN	1.571 (5.858)***	0.227 (2.229)*	0.003 (0.492)	18.873***	0.466
FMCG	1.256 (8.823)***	0.267 (2.364)*	–0.015 (–1.358)	5.761**	0.185
IT	1.601 (6.532)***	0.175 (1.174)	0.001 (0.082)	7.792**	0.263
MEDIA	1.417 (5.236)***	0.693 (3.613)**	–0.058 (–2.476)*	9.797***	0.286
METAL	1.311 (5.856)***	0.311 (2.685)*	–0.009 (–0.881)	16.196***	0.438
PHARMA	1.179 (5.998)***	0.195 (1.502)	0.014 (1.109)	26.872***	0.611
REALTY	1.457 (5.724)***	0.246 (1.776)	0.014 (1.059)	29.001***	0.566
ENERGY	1.208 (3.950)***	0.324 (1.716)	0.004 (0.216)	13.973***	0.382
SERVICES	1.502 (6.602)***	0.266 (2.443)*	0.003 (0.408)	25.102***	0.534
INFRA	1.826 (8.613)***	–0.272 (–1.056)	0.117 (2.435)*	8.584**	0.265

Source: The authors.

Notes: *t*-Statistics are given in parentheses. ***, ** and * Indicate significance at 0.001, 0.01 and 0.05, respectively.

non-presence of herding behaviour in respective sectors. The value of adjusted *R*-square is in the range of 9–37 per cent, implying appropriateness of the model for all sectors. *F*-test statistic gives significant results, indicating all models corresponding to sectors have an overall good fit.

Panel C of Table 7 presents the results of the regression model industry-wise during the COVID-19 outbreak in India. The estimated coefficient γ_2^{Down} of the regression model for MEDIA industry indicates that investors are intended to

herding behaviour in this industry. According to PHD Chamber of Commerce and Industry report, media has been one of the most badly affected sectors due to the COVID-19 pandemic. The Electronic media experienced a heavy loss in advertisement revenues; the outdoor media got all orders cancelled, owing to no traffic on roads due to lockdown; and the events business drew a blank as there were no events permitted in prevailing conditions of COVID-19. These falling advertising revenue trends are expected to pose a significant threat to the industry as advertisement is a prime source of revenue for the media. Therefore, it seems the outbreak of COVID-19 causes sell-side herding behaviour in media and entertainment industry. Moreover, the results of panel C provided weak evidence of herding behaviour during the coronavirus outbreak.

VII. Conclusion and Implications

The ongoing deadly COVID-19 outbreak has wreaked havoc on all world economies as well as weakened the stock markets' performance and hurt the sentiments of stock market participants. This article examined the herding behaviour in the Indian stock market in the prevalence of the COVID-19 pandemic. We argued that pandemic turmoil causes extreme market conditions and fuels panic among the market participants. Using daily data from the national stock exchange (NSE), we deployed different models to investigate the industry herding behaviour among investors under different market conditions and time horizons. Using the different models proposed by Chang et al. (2000), we examined the herding behaviour in general, in the pre- and post-COVID-19 outbreak, and during both bull and bear market conditions.

Our results of this article for the whole sample and before the COVID-19 outbreak period failed to provide the general evidence of herding behaviour for all industries, but they did suggest strong evidence of anti-herding behaviour for Banking, Financial Services, Metal, Pharmaceutical, Realty, Energy, Services and Infrastructure industry that also showed non-linearity. Therefore, our findings are consistent with Kumar et al. (2016), Dutta et al. (2016) and Ganesh et al. (2016), who recently tested the herding behaviour in the Indian stock market and suggested that Indian equity market is generally free of industrial herding and even when they showed some level of herding. But our findings contradict with Lao and Singh (2011), who suggest the presence of herding behaviour in the Indian stock market. The rationale of our findings being inconsistent with Lao and Singh (2011) is threefold. First, we detect the herding behaviour at the industry level, whereas Lao and Singh (2011) observe the herding behaviour at the market level. Second, Lao and Singh (2011) used the data of top 300 firms from the Bombay Stock Exchange index (BSE) over the period from 1 July 1999 to 30 June 2009 to observe the herding behaviour, and during the study period, Indian stock market could be inefficient. On the other hand, we used the latest data of 12 industries from the NSE over the period from 1 January 2015 to 1 June 2020 to investigate the herding behaviour. Third, in recent years, market regulator, that is Securities

and Exchange Board of India (SEBI) has attempted to maintain information symmetry that has resulted in informed decision-making by the shareholders.

Furthermore, during the bull market conditions, we found weak evidence of herding for the whole sample and pre-coronavirus pandemic period. But, the post-COVID-19 pandemic period provided strong evidence of herding behaviour for the automobiles, IT and pharmaceutical industry in bullish market conditions. Further, in the bearish market conditions, our results suggest the presence of herding behaviour during the post-COVID-19 outbreak period for the media and entertainment industry. Therefore, it seems the outbreak of COVID-19 causes herding behaviour in the automobile industry, IT, pharmaceutical and media and entertainment industry.

This article has certain relevant implications for investors, policymakers and market regulators in market turbulence phase like the COVID-19 pandemic. For a fair valuation of financial assets, market participants should consider the role of herding in the selection of assets. Knowledge of herding behaviour at the industry level helps individual investors in the pursuit of making sensible and effective financial decisions in the regime of the COVID-19 pandemic. Herding behaviour encourages market participants to invest in risky assets that may fuel market volatility. Easily accessible and quality information helps investors in the selection of risky assets. During the turbulence period, market regulators should issue guidelines to listed entities for full disclosure of qualitative and quantitative information regarding associated risk that listed entities are exposed to. Similarly, the Indian stock market regulator, Securities and Exchange Board of India (SEBI), has recently advised listed companies to make suitable disclosures regarding the economic impact of COVID-19 on its operations as part of its disclosure obligations to shareholders and investors.

Further, this study facilitates regulators who aim to bring back efficiency in the stock market and control volatility. To control volatility in the market during an environment of panic and fear like COVID-19 pandemic, the market regulator can issue various measures such as ensuring orderly trading and settlement, restrictions of positions and increased margins, enhanced margins for volatile stocks and reduced market-wide position limits for volatile scripts. We have investigated the presence of herding behaviour using the measure proposed by Chang et al. (2000) and provided *F*-test and adjusted *R*-square values as diagnostics. Therefore, future researchers could use other diagnostics of OLS estimation with outcomes for the robustness of results. Future researchers could use trading volume as a proxy variable to observe the herding behaviour.

Acknowledgements

The authors are grateful to the editor of Millennial Asia and the anonymous referees for their extremely useful suggestions to improve the quality of the article. All usual disclaimers apply.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors received no financial support for the research, authorship and/or publication of this article.

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