APPLIED FINANCE LETTERS

VOLUME 09, 2020

DOES HERDING EXIST IN LOTTERY STOCKS? EVIDENCE FROM THE INDIAN STOCK MARKET

ALEEM ANSARI*, TARIQ AZIZ, VALEED AHMAD ANSARI

Aligarh Muslim University, Aligarh, India

* Corresponding Author: Aleem Ansari, Department of Business Administration, Aligarh Muslim University, Aligarh, India 1, Muzammil Hostel, V.M. Hall, Aligarh Muslim University, Aligarh, India
☎ +91-7417809800 ✉ aansari108@myamu.ac.in

Abstract:

In this paper, we investigate the presence of herd behaviour among lottery stocks using Max, skewness and idiosyncratic volatility in the Indian stock market during the period January 2000 to December 2018. We demonstrate that the herd behaviour is non-existent across proxies of lottery-stocks MAX and skewness and find that the herd behaviour is present among highly idiosyncratic stocks. This sheds light on why herding is not detected in the prior studies as it may be concentrated among stocks with certain characteristics. Further, it provides evidence of adverse herding.

Keywords: Herd behaviour, lottery-stocks, emerging markets

JEL classification: G15

1. Introduction

The word herd is described in the Cambridge dictionary as "to make animals move together as a group." In the financial market, investors and fund managers also move together in groups, to take a decision regarding buying and selling assets in the market. When investors are influenced by other's action and imitates their behaviour ignoring their own information, it is termed as herd behaviour in the financial lexicon (Devenow and Welch, 1999). The herd behaviour of investors may lead to excess volatility and fragility to the financial market, etc. (Bikhchandani and Sharma, 2000).

There are voluminous studies examining herd behaviour in the developed and emerging markets (Christie and Huang 1995; Chang et al., 2000; Hwang et al., 2004; Demirer and Kutan 2006; Tan et al., 2008; Chiang and Zheng 2010; Economou et al. 2011; Kapusuzoglu 2011; Clements, Hurn & Shi., 2017). These studies capture herding behaviour based on different market states. Existing studies in the Indian equity market reported absence of herding behaviour for normal stocks (non-lottery types) under different market conditions (extreme upper tail and lower tail, up and down markets) (Lakshman et al., 2011; Lao and Singh, 2011; Saumitra and Sidharth, 2012; Patro and Kanagaraj, 2012; Prosad et al., 2012; Garg and Gulati, 2013; Poshakwale and Mandal, 2014). One of the probable reasons why these studies didn't detect the herding behaviour is that it may be confined in a particular sub-set of the stocks instead of the overall market (Fama and French, 2008; Aziz and Ansari, 2017). Especially, stocks which attract retail and individual investors like lottery stocks (Kumar, 2009) may be the ideal candidate to be examined for the presence of herding behaviour (Rahman et al. 2015).

Following the same intuition, Gong and Dai (2018), examine the presence of herd behaviour in the lottery-type stocks in the Chinese market and find that investors exhibit stronger herding behaviour in such stocks. The novelty and recentness of the reported empirical phenomenon motivate us to probe the herd behaviour in lottery-type stocks in Indian stock market.

Kumar (2009) argues that investors perceive low-priced stocks with high idiosyncratic volatility and idiosyncratic skewness as lotteries. In addition, Bali, Cakici, and Whitelaw (2011) proposed extreme positive returns as a proxy for lottery-type stocks. Following Kumar (2009) and Bali et al. (2011), we take idiosyncratic volatility, skewness, and extreme positive returns as empirical proxies for lottery-type stocks and examine the investor herd behaviour in such stocks.

The results suggest that the herd behaviour is non-existent in lottery-type stocks as proxied by, Max, and skewness. However, some evidence of herding was found during up market condition for high idiosyncratic stocks in the Indian equity market. This finding is consistent with the prior studies in the Indian context for normal stocks. This study fills the empirical void for the presence of herd behaviour in lottery stocks for the Indian stocks market. Rest of the paper is organized as follows: Section 2 discusses the data and methods employed; Section 3 presents the main results and Section 4 contains concluding remarks.

2. Data and Methods

Daily closing prices have been obtained for the constituent companies of S&P BSE500 index from ProwessIQ, a database maintained by Centre for Monitoring Indian Economy (CMIE) for the period January 2000 to December 2018. Each month from January 2000 to December 2018 stocks are segregated into three groups based on a proxy of lottery stocks i.e. MAX, Skewness, and idiosyncratic volatility. Herding is tested separately for each group to check the pervasiveness of the herding behaviour across lottery and non-lottery stocks. MAX is computed as follows:

$$Max_{i,t} = Max(R_{i,d}), d = 1, \dots D_t \quad (1)$$

where, $R_{i,d}$ is the daily return of stock *i* on day *d*, and D is the number of days in month *t*. Three versions of Max are computed following Bali et al. (2011) i.e. Max(1), Max(2), and Max(3), where Max(2) is the average of two maximum daily returns in a month and Max(3) is the average of three largest returns in a month. Skewness of a stock is calculated as:

$$Skew_{i,t} = \frac{1}{D_t} \sum_{d=1}^{Dt} \left(\frac{r_{i,d} - \mu_i}{\sigma_i} \right)^3 \quad (2)$$

Skewness of each stock is computed over a window of one (Skew(1)) and three months (Skew(3)). Idiosyncratic volatility is computed relative to the Carhart's (1997) model:

$$R_{i,d} - Rf_d = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \varepsilon_t. \quad (3)$$

Idiosyncratic volatility is defined as the standard deviation of the error term in eq 3:

$$IVOL_{i,t} = \sqrt{var(\varepsilon_{i,d})} \quad (4)$$

The factors were obtained from the data library of Agrwalla, Jacob and Varma (2014). IVOL is computed over a window of one (IVOL(1)) and three months (IVOL(3)). After computing the lottery proxies and segregating the sample each month into three groups based on it, we followed Christie and Huang (1995) and Chang, Cheng, and Khornan (2000) to test for the presence of the herd behaviour across these groups.

Following Christie and Huang (1995), we examine the extreme tails of the market return to capture herding behaviour using cross-sectional standard deviation (CSSD):

$$CSSD_t = \frac{\sqrt{\sum_{i=1}^{N}(R_{it}-R_{mt})}^2}{N-1} \quad (5)$$

where R_{it} is the return of stock *i* at time *t* and R_{mt} is the cross-sectional mean of the N returns in the sample. Taking $CSSD_t$ as the dependent variable, a regression equation is formed below to detect herding behaviour.

$$CSSD_t = \alpha + \beta^L D^L{}_t + \beta^U D^U{}_t + \varepsilon_t \quad (6)$$

The negative coefficient of β^L and β^U signifies the presence of herding behaviour in the extreme lower and extreme upper tail of return distribution. The extremes are defined at 10, 5, and 1 percentiles.

Chang, Cheng, and Khorana's (2000) model uses cross-sectional absolute deviation (CSAD) to measure herding behaviour in up and down market condition:

$$CSAD_t = \frac{1}{N}\sum_{i=0}^{n}|R_{i,t} - R_{m,t}| \quad (7)$$

where R_{it} is the return of a particular stock at time *t* and R_{mt} is the average market return at time *t*. CSAD is regressed on absolute values of market return and its square to detect the herd behaviour:

$$CSAD_t = \alpha + \beta_1|R_{m,t}| + \beta_2|R_{m,t}^2| + \varepsilon_t \quad (8)$$

In normal market condition, the coefficient β_2 is expected to be positive and statistically significant as per rational asset pricing model. However, during extreme market conditions, a significant negative coefficient of R^2_{mt} would constitute as evidence of investors' herd behaviour. To account for the possible asymmetric effects of herding behaviour during up and down market conditions, the following empirical model is used:

$$CSAD_t = \alpha + \beta_1 (1-D)\left|R_{m,t}\right| + \beta_2 (D)\left|R_{m,t}\right| + \beta_3 (1-D)R^2_{m,t} + \beta_4 (D)R^2_{m,t} + \varepsilon_t \quad (9)$$

where, D = 1 if R_{mt}<0, and D = 0 if Rm_t>0. In other words, the model is estimated separately for the down and upmarket conditions. A negative and significant coefficient β_3 in the model is considered as an evidence of herding in the upmarket and negative β_4 signifies herding in the down market.

3. Results

Table 1 reports the results based on Christie and Huang's (1995) methodology of cross-sectional standard deviation (CSSD) described in equation 6 for 10, 5, and 1 percent criteria. The sample is sorted into three groups based on Max, skewness, and idiosyncratic volatility. Panel A of Table 1 shows that coefficients of βU (upper tail) and βL (lower tail) are significantly positive for all definitions of tails i.e. 10, 5, and 1 percent, for Max (1), Max (2), and Max (3), which suggests the absence of herding behaviour. This suggests an increase in equity return dispersion with respect to market return during the extreme low and up markets. Furthermore, the results of skewness (Panel B) also don't show any evidence of herding behaviour, as the coefficient of βU and βL are positive and significant for all the three definitions of up and down markets. In the case of idiosyncratic volatility, we find a negative and significant coefficient of βU (at 1 and 5% significance level) and βL (at 5 and 10% significance level) for high idiosyncratic volatility stocks (IVOL(3)) at 10 and 5 percent criteria. The phenomenon is however absent when IVOL is computed using one-month data. Overall, the results show the presence of herding behaviour in highly idiosyncratic stocks.

Table 2 and 3 provide the results based on Chang, Cheng and Khorana's (2000) method of cross-sectional absolute deviation (CSAD) explained in equation 8 and 9. In table 2, the coefficients β_2 for max, skewness, and idiosyncratic volatility based groups are positive and significant at the 1 percent level, indicating the absence of herding. On the contrary, it suggests presence of adverse herding (Gebka and Wohar, 2013). Table 3 reports a similar result based on equation 9 under different market conditions for all max, skewness, and idiosyncratic volatility-based groups of stocks. The coefficients of β_3 (upmarket condition) and β_4 (down market) are positive and significant at the 1 percent level indicating an increase in return dispersion in relation to market return during the extreme market conditions. Overall, the results suggest the absence of herding behaviour across stocks with low and high values of max and skewness using both major methods of testing the herd behaviour. For idiosyncratic volatility, the results show the presence of herding in highly idiosyncratic stocks.

Table 1: Regression results of the daily CSSD for stocks sorted on max, skewness and idiosyncratic volatility

		Panel A: Max								
					10%		5%		1%	
		α_0	β_U	β_L	α_0	β_U	β_L	α_0	β_U	β_L
Max (1)	**Low**	0.0228 (89.06)[a]	0.0031 (4.97)[a]	0.0030 (4.41)[a]	0.0229 (91.83)[a]	0.0056 (6.00)[a]	0.0048 (4.71)[a]	0.0231 (92.33)[a]	0.0123 (5.30)[a]	0.0123 (4.73)[a]
	Med	0.0265 (44.51)[a]	0.0050 (1.61)	0.0037 (3.71)[a]	0.0269 (41.75)[a]	0.0034 (3.47)[a]	0.0061 (4.18)[a]	0.0271 (44.97)[a]	0.0088 (4.53)[a]	0.0174 (4.90)[a]
	High	0.0311 (67.12)[a]	0.0025 (3.46)[a]	0.0027 (2.92)[a]	0.0313 (70.36)[a]	0.0032 (3.39)[a]	0.0047 (3.57)[a]	0.0314 (73.05)[a]	0.0082 (3.96)[a]	0.0142 (4.29)[a]
Max (2)	**Low**	0.0226 (91.12)[a]	0.0030 (4.99)[a]	0.0030 (4.19)[a]	0.0227 (93.03)[a]	0.0052 (5.86)[a]	0.0051 (4.58)[a]	0.0230 (94.23)[a]	0.0123 (5.34)[a]	0.0135 (4.11)[a]
	Med	0.0260 (43.79)[a]	0.0024 (3.00)[a]	0.0039 (4.08)[a]	0.0261 (48.20)[a]	0.0042 (4.35)[a]	0.0065 (4.85)[a]	0.0264 (51.74)[a]	0.0093 (5.05)[a]	0.0168 (5.56)[a]
	High	0.0316 (67.43)[a]	0.0051 (1.66)[c]	0.0024 (2.56)[b]	0.0321 (56.47)[a]	0.0026 (2.69)[a]	0.0041 (3.03)[a]	0.0322 (59.42)[a]	0.0076 (3.49)[a]	0.0136 (4.17)[a]
Max (3)	**Low**	0.0226 (91.02)[a]	0.0029 (4.94)[a]	0.0030 (4.15)[a]	0.0227 (93.47)[a]	0.0049 (5.74)[a]	0.0051 (4.58)[a]	0.0229 (94.74)[a]	0.0123 (5.39)[a]	0.0139 (4.26)[a]
	Med	0.0259 (43.79)[a]	0.0024 (3.04)[a]	0.0040 (4.03)[a]	0.0260 (48.09)[a]	0.0045 (4.51)[a]	0.0066 (4.72)[a]	0.0263 (51.57)[a]	0.0097 (5.01)[a]	0.0177 (5.60)[a]
	High	0.0317 (67.77)[a]	0.0051 (1.65)	0.0023 (2.60)[a]	0.0321 (56.67)[a]	0.0025 (2.63)[a]	0.0040 (3.01)[a]	0.0323 (56.70)[a]	0.0072 (3.39)[a]	0.0125 (3.94)[a]
		Panel B: Skewness								
Skew (1)	**Low**	0.0271 (44.81)[a]	0.0022 (2.63)[b]	0.0029 (2.98)[a]	0.0271 (48.93)[a]	0.0042 (3.91)[a]	0.0054 (3.86)[a]	0.0273 (52.46)[a]	0.0100 (4.40)[a]	0.0167 (4.23)[a]
	Med	0.0267 (82.47)[a]	0.0056 (1.86)[c]	0.0035 (4.35)[a]	0.0272 (57.93)[a]	0.0040 (4.53)[a]	0.0055 (4.35)[a]	0.0274 (61.14)[a]	0.0104 (4.91)[a]	0.0149 (4.80)[a]
	High	0.0277 (76.07)[a]	0.0024 (3.99)[a]	0.0028 (3.35)[a]	0.0278 (79.51)[a]	0.0035 (4.29)[a]	0.0047 (4.08)[a]	0.0280 (81.98)[a]	0.0084 (4.41)[a]	0.0126 (4.79)[a]
Skew (3)	**Low**	0.0264 (75.30)[a]	3.52E-06 (0.00)	-2.75E-05 -(0.04)	0.0263 (76.45)[a]	0.0002 (0.28)	-0.0001 -(0.11)	0.0263 (78.15)[a]	0.0030 (2.00)[b]	0.0040 (2.03)[b]
	Med	0.0277 (54.55)[a]	-0.0008 -(1.30)	-0.0004 -(0.53)	0.0277 (57.69)[a]	-0.0008 -(1.06)	-0.0007 -(0.78)	0.0275 (60.86)[a]	0.0014 (0.88)	0.0024 (1.12)
	High	0.0290 (46.16)[a]	-(0.0003 -(0.35)	-0.0008 -(0.99)	0.0289 (50.54)[a]	-0.0007 -(0.75)	-0.0004 -(0.41)	0.0289 (53.85)[a]	9.55E-05 (0.06)	0.0020 (0.88)
		Panel C: Idiosyncratic volatility								
IVOL (1)	**Low**	0.0222 (87.22)[a]	0.0027 (4.64)[a]	0.0031 (4.26)[a]	0.0223 (89.77)[a]	0.0049 (5.81)[a]	0.0053 (4.90)[a]	0.0225 (90.98)[a]	0.0110 (4.83)[a]	0.0127 (4.82)[a]
	Med	0.0253 (91.33)[a]	0.0060 (1.98)[c]	0.0040 (4.90)[a]	0.0258 (58.34)[a]	0.0045 (4.80)[a]	0.0061 (4.64)[a]	0.0260 (61.71)[a]	0.0105 (5.93)[a]	0.0167 (4.91)[a]
	High	0.0325 (46.41)[a]	0.0017 (1.92)[c]	0.0021 (1.97)[b]	0.0326 (50.44)[a]	0.0025 (2.41)[b]	0.0042 (2.94)[a]	0.0327 (53.72)[a]	0.0073 (3.26)[a]	0.0145 (3.91)[a]
IVOL (3)	**Low**	0.0216 (84.55)[a]	0.0009 (1.68)[c]	0.0012 (1.98)[b]	0.0217 (83.64)[a]	0.0010 (1.39)	0.0014 (1.67)[c]	0.0217 (85.26)[a]	0.0026 (2.64)[b]	0.0050 (2.48)[b]
	Med	0.0260 (55.78)[a]	0.0003 (0.56)	-0.0004 -(0.54)	0.0261 (57.64)[a]	0.0003 (0.36)	-0.0004 -(0.58)	0.0260 (60.88)[a]	0.0030 (1.76)[c]	0.0030 (1.69)[c]
	High	0.0337 (47.30)[a]	-0.0022 -(2.69)[a]	-0.0018 -(1.98)[c]	0.0335 (51.09)[a]	-0.0023 -(2.49)[b]	-0.0018 -(1.63)[c]	0.0332 (53.93)[a]	-0.0005 -(0.30)	0.0010 (0.41)

This table reports the results of the model (6) for three groups of stocks formed on the basis of a proxy of lottery-likeliness. Figures in parentheses are t-statistics based on Newey-West (1987) consistent standard errors. Subscripts (a), (b), and (c) represent statistical significance at 1, 5, and 10 percent levels, respectively.

Table 2: **Regression results of the daily *CSAD* for portfolios sorted on max, skewness and idiosyncratic volatility**

		α_0	β_1	β_2
Panel A: Max				
Max (1)	**Low**	0.0129 (62.56)[a]	0.4418 (11.30)[a]	6.5133 (5.25)[a]
	Med	0.0151 (53.82)[a]	0.5331 (10.33)[a]	9.38 (5.82)[a]
	High	0.0182 (56.23)[a]	0.6085 (12.11)[a]	8.5982 (5.97)[a]
Max(2)	**Low**	0.0127 (61.48)[a]	0.4303 (10.62)[a]	6.8034 (5.20)[a]
	Med	0.0149 (58.11)[a]	0.5321 (11.58)[a]	8.9597 (6.35)[a]
	High	0.0185 (53.70)[a]	0.6258 (11.48)[a]	8.6648 (5.41)[a]
Max (3)	**Low**	0.0126 (59.71)[a]	0.4195 (9.89)[a]	7.2075 (5.14)[a]
	Med	0.0148 (58.13)[a]	0.5482 (11.84)[a]	8.4042 (6.05)[a]
	High	0.0187 (53.83)[a]	0.6226 (11.73)[a]	8.8075 (5.74)[a]
Panel B: Skewness				
Skew(1)	**Low**	0.0150 (56.34)[a]	0.5158 (11.00)[a]	8.9171 (5.89)[a]
	Med	0.0155 (56.36)[a]	0.5417 (11.46)[a]	7.9834 (5.66)[a]
	High	0.0157 (62.73)[a]	0.5361 (11.47)[a]	7.4446 (5.26)[a]
Skew (3)	**Low**	0.0145 (59.13)[a]	0.5403 (11.51)[a]	7.5032 (4.78)[a]
	Med	0.0155 (59.85)[a]	0.5133 (11.89)[a]	8.3864 (6.37)[a]
	High	0.0156 (56.38)[a]	0.5234 (9.15)[a]	8.6060 (4.92)[a]
Panel C: Idiosyncratic risk				
IVOL (1)	**Low**	0.0125 (63.25)[a]	0.3756 (9.62)[a]	6.9588 (5.51)[a]
	Med	0.0148 (59.84)[a]	0.5532 (12.07)[a]	8.4382 (6.04)[a]
	High	0.0188 (53.32)[a]	0.6584 (12.15)[a]	9.0367 (5.70)[a]
IVOL (3)	**Low**	0.0120 (66.77)[a]	0.3351 (9.01)[a]	7.521 (6.20)[a]
	Med	0.0146 (59.02)[a]	0.5430 (10.99)[a]	8.7072 (5.46)[a]
	High	0.0189 (54.73)[a]	0.6947 (12.82)[a]	8.3082 (5.26)[a]

This table reports the estimates of model 8. Figures in parentheses are t-statistics based on Newey-West (1987) consistent standard error. Subscripts [a], [b], and [c] represent statistical significance at 1, 5, and 10 percent levels, respectively

Table 3: Regression results of the daily *CSAD* for portfolios sorted on max, skewness and idiosyncratic volatility under up and down markets.

		α_0	β_1	β_2	β_3	β_4
Panel A: Max						
Max (1)	**Low**	0.0129 (60.75)[a]	0.3965 (7.79)[a]	0.4804 (10.93)[a]	7.5409 (3.66)[a]	5.6569 (4.07)[a]
	Med	0.0152 ((45.51)[a]	0.4632 (4.69)[a]	0.5799 (10.89)[a]	12.71 (2.88)[a]	7.4202 (4.75)[a]
	High	0.0183 (55.29)[a]	0.5415 (7.84)[a]	0.6698 (12.76)[a]	9.5598 (3.54)[a]	7.5380 (5.33)[a]
Max (2)	**Low**	0.0128 (58.77)[a]	0.3931 (7.00)[a]	0.4623 (10.56)[a]	7.6103 (3.22)[a]	6.1135 (4.42)[a]
	Med	0.0150 (52.48)[a]	0.4591 (6.08)[a]	0.5858 (11.65)[a]	11.7932 (3.63)[a]	7.1427 (4.70)[a]
	High	0.0186 (50.96)[a]	0.5557 (6.49)[a]	0.6852 (12.65)[a]	10.3157 (2.86)[a]	7.3162 (5.14)[a]
Max (3)	**Low**	0.0127 (56.87)[a]	0.3887 (6.51)[a]	0.4466 (9.94)[a]	7.7930 (3.03)[a]	6.6665 (4.61)[a]
	Med	0.0149 (52.90)[a]	0.4773 (6.41)[a]	0.6007 (12.13)[a]	11.0945 (3.46)[a]	6.6621 (4.67)[a]
	High	0.0188 (51.14)[a]	0.5462 (6.57)[a]	0.6860 (12.76)[a]	10.7853 (3.14)[a]	7.2719 (5.11)[a]
Panel B: Skewness						
Skew (1)	**Low**	0.0151 (52.01)[a]	0.4298 (5.69)[a]	0.5791 (11.64)[a]	12.2609 (3.70)[a]	6.7735 (4.33)[a]
	Med	0.0155 (51.73)[a]	0.4768 (6.14)[a]	0.5939 (12.39)[a]	9.9020 (3.00)[a]	6.5899 (4.95)[a]
	High	0.0157 (62.05)[a]	0.5068 (8.18)[a]	0.5665 (12.17)[a]	7.39 (2.92)[a]	7.1552 (5.66)[a]
Skew (3)	**Low**	0.0146 (58.61)[a]	0.4589 (7.74)[a]	0.6048 (11.04)[a]	10.0487 (4.18)[a]	5.7003 (3.02)[a]
	Med	0.0155 (55.68)[a]	0.4595 (6.63)[a]	0.5521 (11.83)[a]	10.5889 (3.56)[a]	7.0028 (4.92)[a]
	High	0.0156 (53.02)[a]	0.5090 (5.87)[a]	0.5376 (10.92)[a]	8.6837 (2.34)[b]	8.4242 (6.43)[a]
Panel C: Idiosyncratic volatility						
IVOL(1)	**Low**	0.0125 (62.29)[a]	0.3446 (7.14)[a]	0.4029 (9.28)[a]	7.2886 (3.71)[a]	6.5294 (4.63)[a]
	Med	0.0148 (53.50)[a]	0.4920 (6.35)[a]	0.5990 (12.51)[a]	10.6987 (3.22)[a]	6.9576 (5.04)[a]
	High	0.0189 (49.70)[a]	0.5697 (6.29)[a]	0.7292 (13.41)[a]	11.7087 (3.05)[a]	7.1141 (5.00)[a]
IVOL (3)	**Low**	0.0121 (65.09)[a]	0.3147 (6.67)[a]	0.3504 (8.11)[a]	8.2655 (4.45)[a]	7.0310 (4.78)[a]
	Med	0.0147 (53.99)[a]	0.4905 (6.39)[a]	0.5812 (10.97)[a]	10.8075 (3.31)[a]	7.3752 (4.29)[a]
	High	0.0190 (50.85)[a]	0.6141 (6.63)[a]	0.7615 (14.84)[a]	10.4506 (2.61)[b]	6.6623 (5.39)[a]

This table reports the regression results for the model (9). Figures in parentheses are t-statistics based on Newey-West (1987) consistent standard error. Subscripts [a], [b], and [c] represent statistical significance at 1, 5, and 10 percent levels, respectively

4. Conclusion

This article explored the presence of herd behaviour in lottery stocks in the Indian stock market. Lottery stocks are proxied by max, skewness, and idiosyncratic volatility. Employing the methods of both Christie and Huang (1995) and Chang, Cheng, and Khorana (2000), we find that the herding behaviour is non-existent across stocks with low and high values of max and skewness. As for the idiosyncratic volatility, the results show the presence of herd behaviour in highly idiosyncratic stocks. However, in general, the results show the evidence of adverse herding or high return dispersion during extreme market conditions for all types of stocks. It may be induced by the presence of novice traders acting on non-fundamental factors or may be driven by overconfidence of investors (Gebka and Wohar, 2013).

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