Theoretical Economics Letters, 2017, 7, 1015-1028
http://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

Herding Behavior in Futures Market: An Empirical Analysis from India

Ameet Kumar Banerjee[1]*, Purna Chandra Padhan[2]

[1]Faculty of Management Studies-WISDOM, Banasthali Vidyapith (University), Banasthali, India
[2]XLRI, Xavier School of Management, Jamshedpur, India
Email: *ameet.banerjee@rediffmail.com

How to cite this paper: Banerjee, A.K. and Padhan, P.C. (2017) Herding Behavior in Futures Market: An Empirical Analysis from India. *Theoretical Economics Letters*, **7**, 1015-1028.
https://doi.org/10.4236/tel.2017.74069

Received: May 23, 2017
Accepted: June 19, 2017
Published: June 22, 2017

Abstract

This study tries to explore the existence of herding behavior of investors in an entirely new asset class, futures, in Indian futures market. For empirical analysis, it uses data of exchanged traded equity futures contracts, a part of futures and options segment of National Stock Exchange (NSE, India) from January 2011 to June 2016. Applying generalized least squares (GLS) regression model, the study found supporting evidences for existence of herd behavior for the study period, especially during macroeconomic news releases, in periods of extremely low (high) trading volume and spillovers from other markets. This analysis of herd behavior is key in understanding the bandwagon effect of investors, which results in inefficient asset pricing. As a policy implication, it is highly relevant to regulatory institutions responsible for efficient functioning of the financial system.

Keywords

Herding Behavior, Cross-Sectional Dispersion, Futures, Generalized Least Square

1. Introduction

Empirical analysis of herding behavior has drawn extensive attention in behavioral finance literature in recent years. Basically herding behavior is termed as convergence behavior, when market participants tend to suppress personal beliefs to follow the bandwagon in trading assets. It's a behavior considered unlikely rational in view of personal preferences in portfolio building, returns expectations and investment horizon; resulting in driving away assets prices from its intrinsic value (Galariotis *et al.* [1]; Nofsinger and Sias [2]), and this divergence in pricing results in creating arbitrage opportunities to earn abnormal profits. The long term implication of herding may be rather alarming! As assets fail to converge to its fundamental value as herding persists in market segments, leading to inefficient and destabilized markets.

Existing substantial literature has primarily focused on the potency of herding behavior on stock markets and reported mixed findings in support of herding behavior (Bekaert *et al.* [3]; Galariotis *et al.* [1]). However, there is paucity of literature on testing herding behavior in emerging markets, as these markets are fast integrating into global financial system, but significant void exists in market and institutional development. In lieu of this, the primary motive of the present study is to bridge the existing gap and provide complete picture of herding behavior in the context of Indian emerging market settings.

The paper attempts to contribute to herding literature in a variety of ways. First, investigating herding behavior in an entirely different class of assets; namely equity index futures. Second, it studies herding behavior following the macroeconomic news announcements, during periods of market stress and spill-over's from other market segments. Third, by studying herding in futures market, as futures market contains information about expected future prices; and hence contributes to return predictability of the underlying asset. Fourth, helping to resolve some of the mixed findings in herding behavior and lastly, to best of our knowledge, this is the first attempt to study this phenomenon in India particularly in futures market as financial engineered assets have seen a quantum leap in terms of trading volume across global financial markets.

Using the methodology as adopted by Christie and Huang [4], we presented evidences of herding behavior around the announcement of macroeconomic news releases, in periods of market stress, during extreme low (high) trading volume, and spillovers' from other market segments as reported in the previous study of Galariotis *et al.* [1]. The remaining paper is organized as follows. Section 2, presents a brief literature review; Section 3, describes the model specification to detect herding behavior in index futures; Section 4 provides the data; Section 5, presents empirical results and lastly summary and conclusions are presented in Section 6.

2. Literature Review

Numerous studies have attempted to understand herding behavior in financial markets (Banerjee [5]; Bikhchandani *et al.* [6]; Welch [7]) reporting that market participants mimic each other's actions *i.e.*, engage in herding disregarding personnel beliefs (Cipriani and Guarino [8]). Lot of academic rigors have gone in to understand herding behavior as Hwang and Salmon [9] argued that herding violates the propositions of efficient market theory, drives asset prices away from the equilibrium as considered by traditional finance theory and that the prices no longer reflect the true valuation of firms, intuitively resulting in a behavior which may cause financial bubbles in stock markets (Banerjee [5]).

In order to understand herding behavior, previous literature has classified herding as; unintentional herding and intentional herding. Bikhchandani and Sharma [10] argued that the former state refers to situation when investors converge to consensus sharing similar set of signal's to make similar investment decisions (Hirshleifer *et al.* [11]) whereas intentional herding is the consequence of investors overtly disregarding personal beliefs to infer from the trading activities of the others in the anticipation that they share superior private information (Shiller *et al.* [12]). Moreover, studies by Hirshleifer and Teoh [13] and Hwang and Salmon [9], argued that intentional herding tend to destabilize asset prices and impair the proper functioning of financial markets.

While herding is explored in different markets but the results of the studies are far from being homogenous. Gleason *et al.* [14] studying nine different exchange traded funds (ETFs) in US markets provided no support for herding behavior whereas studies in emerging markets by Chang *et al.* [15] posited significant herding behavior in South Korean and Taiwanese markets and whereas to lesser extent in Japan. Chiang and Zheng [16] tested herding behavior in 28 different markets found evidences of herding in many advance economies and Asian countries exception being the US and the Latin American markets. Blassco and Ferreruela [17] examined herding behavior in seven different countries and found supporting evidences of herding behavior only in Spain among the sampling countries.

Further, empirical studies by Galariotis *et al.* [1] for leading U.S and U.K stock reported herding behavior by US investors in periods of release of macroeconomic information and the herding spill-over from the U.S to the U.K in periods of turmoil's. While Borensztein and Gelos [18] study on mutual funds of emerging markets, provided evidences of herd behavior, as result of different market conditions, whereas Zhou and Anderson [19] investigated herding behavior using quantile regression in US real market reported that investors herd under turbulent market conditions, in addition, they found asymmetric effect of herding in declining markets than in rising markets. **Table 1** presents a comprehensive review of herding behavior from different markets.

3. Model Specification

Like most of the former studies, herding behavior towards market consensus was analyzed using cross-sectional dispersion of returns (Christie and Huang [4]; Galariotis *et al.* [1]). Though these measures were explored for herding effects in stock markets not in futures market; and in order to accommodate for some of the unique market microstructure of futures market which sets them apart from that of the stock markets, we have modified the established methodology for the study. As posited by Christie and Huang [4] when stock returns herd around the market consensus, the returns dispersions should be moderately low and under hypothetical perfect herding conditions all stocks offers exactly the returns as that of the market index *i.e.* $R_{i,t} = R_{mkt,t}$. Using similar analogy, we tested herding behavior in stock index futures by calculating cross-sectional absolute deviation (hereafter CSAD) as

$$CSAD_t^F = \frac{\sum_{t=1}^{N}\left|R_t^{S,F} - R_{mkt,t}^{I,F}\right|}{n} \tag{1}$$

Table 1. Summary of literature review.

Summary of literature review		
Author(s)	Data Frequency	Main findings
Lakonishok *et al.* [20]	Quarterly	The study presents negative evidences of herding among US pension fund managers.
Nofsinger and Sias [2]	Monthly	The results of the study reported herding behavior among institutional and individual investors. And, institutional investors herding affect prices more than the individual investors.
Choe *et al.* [21]	Daily	Found support for herding behavior by foreign investors in Korean stock market. Although herding behavior has not contributed to destabilization of prices for the entire period of study.
Oehler and Chao [22]	Daily	Reported evidences of strong herding behavior in German bond markets and specially the herding behavior was found stronger in stock market than in bond markets
Hwang and Salmon [9]	Daily	The study evidences of herding behavior in US and Korean market and against widely believed herding falls during Asian and Russian crises period.
Kim and Nofsinger [23]	Monthly	The empirical study reported herding behavior in Japan and presented evidences of large price movements in stock market as a result of herding.
Wylie [24]	Half yearly	The study reported significant herding behavior among fund managers especially in UK large and small stocks
Demirer and Kutan [25]	Daily	The study examined herding behavior in Chinese market using both firm and sectorial level data. The findings of the study indicate negative evidences of herding in Chinese stock markets.
Caporale *et al.* [26]	Daily, weekly and monthly	Provided evidences of herding behavior in Athens stock market
Caparrelli *et al.* [27]	Daily	The study reported herding under extreme market conditions in Italian stock market.
Chiang and Zheng [16]	Daily	The study investigated herding behavior in Chinese stock markets. And the results of the study reported, evidences of herding in both Shanghai and Shenzhen A share market and no evidences of herding was reported in B share market
Fu and Lin [28]	Monthly	Reported evidences of herding behavior Chinese stock market and herding are more prevalent in up markets than in down markets.
Kremer and Nautz [29]	Daily	This paper investigated herding behavior in German stock market. Using a comprehensive database the study provided evidences of herding behavior among institutional investors and the intensity of herding depending on the stock characteristics.
Galariotis *et al.* [1]	Daily	The study investigated herding behavior toward market consensus for leading stocks of US and UK markets. The results indicate herding behavior during release of macroeconomic information and spillover effect from US to UK market.

where $R_t^{S,F}$ are the average daily returns of the individual stock futures part of NSE Nifty fifty index and $R_{mkt,t}^{I,F}$ are the returns of Nifty fifty stock index futures at time t, and n is the cross-section of individual stock futures.

In order to detect herding behavior a generalized linear regression (GLS) model is used by regressing cross-sectional dispersion against index futures returns and a set of variables which are proxy for macroeconomic news releases, market stress and spill-over's from other market segments. This approach is preferred over ordinary least square (OLS) as GLS is found more adaptive when the error and the dependent variable fails to conform to Gaussian settings and the presence of heteroscedasticity in the sample data, in such case OLS can significantly distort the estimated results. In addition, as argued by Chang *et al.* [15] that during periods of large price movements the relationship between dispersion and market return is non-linear. Following from the previous studies, in order to capture non-linearity in predictor variables a modified generalized regression model is adopted with following specification

$$CSAD_t^F = \beta_0 + \beta_1 (1 - D_t) R_{mkt,t}^{I,F} + \beta_2 D_t R_{mkt,t}^{I,F} + \beta_3 (1 - D_t) \left(R_{mkt,t}^{I,F}\right)^2 + \beta_4 D_t \left(R_{mkt,t}^{I,F}\right)^2 + \beta_5 D_t^u + \beta_6 D_t^l + \sum_{i=7}^{n} \beta_i X_t + \varepsilon_t \quad (2)$$

were X_t is representative of vector of explanatory variables; D_t is a dummy variable taking the value of 1 if the index returns is $R_{mkt,t}^{I,F} < 0$ and zero otherwise, as investors react differently under different market conditions (Conrad *et al.* [30]; Bekaert and Wu [31]) in order to test the asymmetric behavior of the investors in different market conditions of up against down markets. A dummy variable $\left(D_t^u\right) D_t^l$ is also introduced in "Equation(2)" that takes a value of 1 if the returns of the index futures lie in the 5% lower (upper) tail of the distribution. And $X_{i,t}$'s are proxies for other class of variables affecting herding behavior consisting of conditions of market stress and uncertainty, trading volume, change in open interest positions and macroeconomic news releases.

Chang *et al.* [15] argued that under normal conditions in accordance to rational asset pricing models return dispersions and market volatility to have linear relationship. As result increase in absolute value of the markets tends to rise individual investors returns. However, Chiang and Zheng [16] argued that linear relationship is violated and non-linearity is noticed as market participants tend to make decision based on market aggregate. Here it is important to note that under no herding condition $\beta_1 > 0$ and $\beta_2 < 0$ and under strict linearity non-linear coefficients terms $\beta_3 = \beta_4 = 0$ and any violation is signal for herding behavior.

Christie and Huang [4], posited that herding under more extreme market conditions, a state where CSAD is significantly lower when the index returns lie in the tails of the distribution, while asset pricing models proposes significantly higher dispersion under extreme market movements as assets offer differential rates being differently sensitive to market signals. In case, of herding under extreme market conditions, the individual assets are more likely to be priced to a larger extent similar to market index. This is consistent with the dummy variables (β_5 *and* β_6) for tail index future returns and under conditions of herding, we expect $\beta_5 < 0$ *and* $\beta_6 < 0$.

As documented by findings of prior studies reporting that uncertainty/surprises associated with macroeconomic news releases affect trading activities of investors around the release dates (Boyd *et al.* [32]; Savor and Wilson [33]). For example, Ederington and Lee [34] had observed volatility pattern in both US interest rate and foreign exchange markets significantly contributed by the scheduled announcements, Hence, to examine herding around macroeconomic announcements a dummy variable D^{macro} is introduced in "Equation (2)" that takes value of 1 on the day of new releases and 0 otherwise with following specification. In case of negative evidences of herding the coefficient of interest is β_7 is positive and statistically significant.

$$CSAD_t^F = \beta_0 + \beta_1(1-D_t)R_{mkt,t}^{I,F} + \beta_2 D_t R_{mkt,t}^{I,F} + \beta_3(1-D_t)\left(R_{mkt,t}^{I,F}\right)^2 + \beta_4 D_t\left(R_{mkt,t}^{I,F}\right)^2 + \beta_5 D_t^u + \beta_6 D_t^l + \beta_7 D_t^{macro} + \varepsilon_t \tag{3}$$

As reported by Christie and Huang [4] and Chiang and Zheng [16] herding is prevalent during market uncertainty/stress. So, to examine whether periods uncertainty/stress of can alter the relation of parameters, herding is tested under uncertainty/stress by incorporating a measure for market uncertainty which is proxied at the market level by the daily returns of the volatility index (hereafter VIX) R_t^{VIX} in "Equation (3)". The following is the modified specification of "Equation (3)"

$$CSAD_t^F = \beta_0 + \beta_1(1-D_t)R_{mkt,t}^{I,F} + \beta_2 D_t R_{mkt,t}^{I,F} + \beta_3(1-D_t)\left(R_{mkt,t}^{I,F}\right)^2 + \beta_4 D_t\left(R_{mkt,t}^{I,F}\right)^2 + \beta_5 D_t^u + \beta_6 D_t^l + \beta_7 D_t^{macro} + \beta_8 D_t^{VIX} + \varepsilon_t \tag{4}$$

In "Equation (4)" non-herding behavior imply the coefficient β_8 to be positive and significant.

Majority of the previous literature has reported the relationship between informational quality, market liquidity and informational asymmetry (Diamond and Verrecchia [35]; Kremer and Nautz [29]), while Diamond and Verrecchia [35] posited higher informational asymmetry in illiquid markets whereas Voronkova and Bohl [36] argued that herding behavior is pronounced in emerging markets with lower quality of information and transparency. To, assess whether trading volume can explain the potency of investors to follow market consensus, disregarding personnel beliefs, natural logarithm of futures trading turnover (Lacs) is added to "Equation (4)" as a measure for trading volume.

Further, two additional dummy variables $D_t^{Vol,l}$ and $D_t^{Vol,u}$ are added to "Equation (4)", which takes the value of 1 if the trading volume of index futures lie in the lower (upper) 5% of the distribution or 0 otherwise to test whether extreme levels of trading volume can influence the trading behavior towards market consensus. The new specification of the model is given in "Equation (5)"

$$CSAD_t^F = \beta_0 + \beta_1(1-D_t)R_{mkt,t}^{I,F} + \beta_2 D_t R_{mkt,t}^{I,F} + \beta_3(1-D_t)\left(R_{mkt,t}^{I,F}\right)^2 + \beta_4 D_t\left(R_{mkt,t}^{I,F}\right)^2 + \beta_5 D_t^u + \beta_6 D_t^l + \beta_7 D_t^{macro} + \beta_8 D_t^{VIX} + \beta_9 TVol_t^{I,F} + \beta_{10} D_t^{Vol,l} + \beta_{11} D_t^{Vol,u} + \varepsilon_t \tag{5}$$

The coefficient of trading volume (β_9) and the extreme levels of trading volume dummies $\beta_{10}(\beta_{11})$ in "Equation (5)" should be positive and insignificant under negative conditions of herding.

Girma and Mougou [37] reported open interest as a measure for divergences of opinion of market participants, whereas Donders *et al.* [38] posited open interest as proxy for information processing. In this paper, the potency of open interest positions in index futures are tested to explore, whether open interest can explain investors clustering. Additionally, to check extreme low (negative) and extreme large (positive) changes in index futures open interest affects cross-sectional dispersion, two dummy variables $D_t^{OI,l}$ and $D_t^{OI,u}$ are introduced taking the value of 1, if the changes in the open interest falls in the lower and upper 5% tails of the distribution or 0 otherwise. The extended specification is given in "Equation (6)"

$$\begin{aligned} CSAD_t^F = {} & \beta_0 + \beta_1 (1 - D_t) R_{mkt,t}^{I,F} + \beta_2 D_t R_{mkt,t}^{I,F} + \beta_3 (1 - D_t) \left(R_{mkt,t}^{I,F} \right)^2 \\ & + \beta_4 D_t \left(R_{mkt,t}^{I,F} \right)^2 + \beta_5 D_t^u + \beta_6 D_t^l + \beta_7 D_t^{macro} + \beta_8 D_t^{VIX} + \beta_9 TVol_t^{I,F} \\ & + \beta_{10} D_t^{Vol,l} + \beta_{11} D_t^{Vol,u} + \beta_{12} OI_t^{I,F} + \beta_{13} D_t^{OI,l} + \beta_{14} D_t^{OI,u} + \varepsilon_t \end{aligned} \quad (6)$$

The coefficient of interest for open interest (β_{12}) and the extreme low (high) changes in open interest dummies $\beta_{13}(\beta_{14})$ in "Equation (6)" should be positive and insignificant under negative conditions of herding behavior.

As previous studies have reported empirical evidences in support of spill over's effects *i.e.* herding in one market is affected by the events in the other market (Chiang and Zheng [16]; Galariotis *et al.* [1]). Following similar analogy, it is tested whether herding in futures market may be associated with the herding behavior in underlying spot market by including cross-sectional absolute deviation $CSAD_t^S$ calculated by the returns of the underlying stock market, where the consensus is proxied by the returns of the S&P CNX Nifty 50 stock index, $R_{mkt,t}^{S,I}$.

In similar spirit of Chiang and Zheng [16], additionally squared spot index returns term $\left(R_{mkt,t}^{S,I} \right)^2$ is included to capture non-linearity associated with futures index markets in "Equation (6)", the extended specification is presented in "Equation (7)"

$$\begin{aligned} CSAD_t^F = {} & \beta_0 + \beta_1 (1 - D_t) R_{mkt,t}^{I,F} + \beta_2 D_t R_{mkt,t}^{I,F} + \beta_3 (1 - D_t) \left(R_{mkt,t}^{I,F} \right)^2 \\ & + \beta_4 D_t \left(R_{mkt,t}^{I,F} \right)^2 + \beta_5 D_t^u + \beta_6 D_t^l + \beta_7 D_t^{macro} + \beta_8 D_t^{VIX} \\ & + \beta_9 TVol_t^{I,F} + \beta_{10} D_t^{Vol,l} + \beta_{11} D_t^{Vol,u} + \beta_{12} OI_t^{I,F} + \beta_{13} D_t^{OI,l} \\ & + \beta_{14} D_t^{OI,u} + \beta_{15} CSAD_t^S + \beta_{16} \left(R_{mkt,t}^S \right)^2 + \varepsilon_t \end{aligned} \quad (7)$$

For "Equation (7)", under alternate hypothesis of no herding the coefficient of cross-sectional dispersion from spot index is negative ($\beta_{15} < 0$) and squared spot index returns equals $\beta_{16} = 0$.

4. Data

For the present study, sample data is collected from the futures and option markets (F & O) segment of National Stock Exchange (NSE) India for all firms' part of S & P CNX Nifty 50 futures index from January 2011 to June 2016. Data includes 50 leading firms from 13 different industries with exchange traded futures contract. While information to relating to macroeconomic news events are obtained from Center for Monitoring Indian Economy (CMIE) economic outlook and reconfirmed from the official releases as reported by Reserve Bank of India (RBI) and Ministry of Statistics and Programme Implementation (MOSPI), Government of India (GOI). The sample data is filtered, by excluding all futures trades with less than 3 days from expiration to isolate herding from expiration day effects, CSAD is computed using daily returns and only nearest to maturity contracts are taken to avoid any liquidity issues.

5. Empirical Results

Figure 1 plots the resulting times series of CSAD and Table 2 reports a summary of descriptive statistics. Figure 1 shows evidences of heterogeneity and

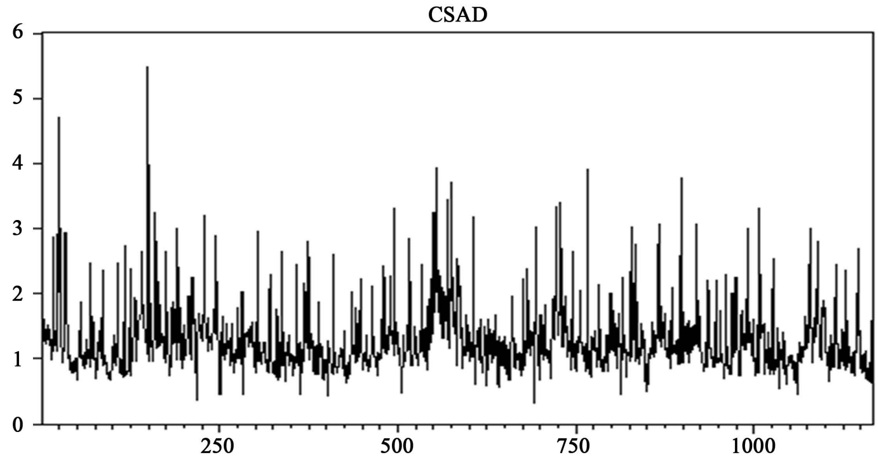

Figure 1. Time series of CSAD. Notes: This figure plots the times series of cross sectional dispersion (CSAD) of futures written on individual stocks around the index futures return and CSAD is measured as $CSAD_t^F = \frac{\sum_{t=1}^{N} \left| R_t^{S,F} - R_{mkt,t}^{I,F} \right|}{n}$, $R_t^{S,F}$ refer to the average daily returns of the individual stock futures part of NSE Nifty fifty index and $R_{mkt,t}^{I,F}$ are the returns of Nifty fifty stock index futures at time t, and n is the cross-section of individual stock futures.

Table 2. Descriptive statistics of daily CSAD.

Details	CSAD
Sample period	01/01/2011-30/06/2016
Number of observations	1166
Mean	1.28
Median	1.16
Min	0.32
Max	5.49
Std. Dev.	0.52
Skewness	2.39
Kurtosis	12.28

Notes: The Table reports the descriptive statistics of the times series of cross sectional dispersion (CSAD) of futures written on individual stocks around the index futures return and CSAD is measured as $CSAD_t^F = \frac{\sum_{t=1}^{N} \left| R_t^{S,F} - R_{mkt,t}^{I,F} \right|}{n}$ $R_t^{S,F}$ refers to the average daily returns of the individual stock futures part of NSE Nifty fifty index and $R_{mkt,t}^{I,F}$ are the returns of Nifty fifty stock index futures at time t, and n is the cross-section of individual stock futures. And the sample data is from January 2011 to June 2016.

confirms the need to test effects of herding in futures market. While **Table 2** reports some of the descriptive statistics for CSAD of index futures contract with mean 1.28 and S.D 0.52, while **Table 3** reports the empirical estimates of "Equation (2)" using GLS model for verifying the evidences of herding in the spirit of Chang *et al.* [15] specification for the near month S & P CNX Nifty 50 futures contract.

Using *EViews* version 9.0, initially, OLS method has been applied to estimate the models, though the results are not reported, however diagnostic checking confirmed violation of classical assumptions of linear regression model. As the model suffered issues of heteroscadasticity; even application of WHCSE and New-Way West consistent SE and covariance did not improve the results. However, GLS method of solving heteroscedasticity, by using estimated residual of OLS as proxy for standard deviation of population error term, shows significant improvement in the results and is consistent with the theoretical hypothesis. Further, Wald's test for coefficient restriction on GLS models rejects null of equality between exploratory variables and Ramsey reset test confirms non-linearity effect on the response variable.

Table 3, Panel (A) contains the estimated coefficients β_1 and β_2 (linear term) synonymous to up (down) markets are positive (negative) and statistically significant at 1% significance level (t-statistics: 35.87 and −82.87) indicating that CSAD tends to increase with stock index futures returns providing negative evidences to herding behavior. While both the coefficient (β_3 and β_4) of $\left(R_t^{mkt}\right)^2$ are found positive and significant at 1% significance level (t-statistics: 35.47 and 4.26) suggesting that CSAD is non-linearly related to futures returns. Moreover, the coefficients β_5 and β_6 representing futures index returns falling in the lower and upper tails of the returns distribution in a particular day are positive and insignificant from **Table 3**, Panel (B). The findings supports that Indian investors actually differ strongly from the market consensus and significantly more so when the consensus takes extreme values. The results are not surprising and quite similar with Chang *et al.* [15] and Demirer and Kutan [25] who reported similar evidences against herding behavior in Hong Kong and Chinese stock markets.

Testing herding augmented by the release of macroeconomic news by performing regression on "Equation (3)" and the results are presented in Panel (C). Note that for the sample the coefficient is negative as hypothesized and statistically significant at 1% significance level (t-statistics: −53.60), thus providing first sign of potential herding behavior Savor and Wilson [33].

The effects of periods of market uncertainty/stress on CSAD as proxied by the daily returns of volatility index (VIX) was estimated using "Equation (4)", the results are presented in Panel (D), the coefficient of interest β_8 is positive and significant at 1% significance level (t-statistics: 70.66), providing negative evidences of herding behavior in periods of volatility/stress in the market.

Panel (E), presents the results of regression "Equation (5)" indicating that the proxy for trading volume is positive and significantly related, thus does not

Table 3. GLS regressions results for NSE CNX Nifty 50 index futures.

	GLS regression results						
Coefficients	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F	Panel G
β_0	1.109 (2230.92)*	1.114 (1972.12)*	1.123 (6732.98)*	1.045 (704.63)*	−3.847 (−51.55)*	3.871 (−74.50)*	−0.500 (−42.19)*
β_1	0.074 (35.87)*	0.068 (32.76)*	0.068 (64.89)*	0.050 (19.47)*	0.011 (2.12)*	0.010 (2.61)*	0.007 (12.58)*
β_2	−0.192 (−82.87)*	0.199 (−41.13)*	−0.193 (−165.21)*	−0.199 (−30.51)*	−0.130 (−26.19)*	−0.141 (−56.66)*	−0.025 (−35.09)*
β_3	0.059 (35.47)*	0.054 (49.23)*	0.053 (225.04)*	0.043 (29.95)*	0.044 (11.94)*	0.041 (14.81)*	−0.006 (−19.35)*
β_4	0.009 (4.26)*	0.05 (2.24)**	0.009 (11.55)*	−0.038 (−9.49)*	−0.024 (−7.96)*	−0.029 (−16.34)*	−0.028 (52.19)*
β_5		0.092 (9.04)*	0.097 (13.42)*	0.141 (25.01)*	0.103 (7.49)*	0.115 (25.04)*	0.003 (3.16)*
β_6		0.079 (77.33)*	0.085 (73.37)*	0.109 (6.53)*	0.147 (6.51)*	0.145 (19.83)*	−0.048 (−49.92)*
β_7			−0.055 (−53.60)*	−0.036 (−14.72)*	−0.037 (−12.71)*	−0.038 (−14.05)*	−0.022 (−28.92)*
β_8				0.027 (70.66)*	0.024 (96.78)*	0.024 (69.62)*	0.001 (34.90)*
β_9					0.196 (65.36)*	0.197 (95.56)*	0.019 (34.66)*
β_{10}					−0.025 (−7.71)*	−0.033 (−10.65)*	0.020 (10.22)*
β_{11}					−0.033 (−10.41)*	−0.033 (−3.55)*	−0.006 (−5.98)*
β_{12}						0.000 (33.47)*	0.000 (32.29)*
β_{13}						0.015 (2.92)*	0.021 (28.15)*
β_{14}						0.019 (3.46)*	−0.007 (−7.16)*
β_{15}							0.996 (2969.81)*
β_{16}							0.000 (35.59)*
R^2	0.997	0.997	0.999	0.997	0.993	0.987	0.999
Adjusted R^2	0.997	0.997	0.999	0.997	0.993	0.987	0.999

*$p < 0.01$; **$p < 0.05$; *$p < 0.10$. Notes: The table reports results based on the following equation using GLS regression modeling:

$$\begin{aligned} CSAD_t^F &= \beta_0 + \beta_1 (1-D_t) R^{I,F}_{mkt,t} + \beta_2 D_t R^{I,F}_{mkt,t} + \beta_3 (1-D_t)\left(R^{I,F}_{mkt,t}\right)^2 \\ &+ \beta_4 D_t \left(R^{I,F}_{mkt,t}\right)^2 + \beta_5 D_t^u + \beta_6 D_t^l + \sum_{i=7}^{n} \beta_i X_t + \varepsilon_t \end{aligned}$$

X_t refer to vector of explanatory variables; D_t is a dummy variable taking the value of 1 if the index returns is $R^{I,F}_{mkt,t} < 0$ and zero otherwise. And $(D_t^u) D_t^l$ are dummies to capture investors asymmetric behaviour in up (down) markets.

support or explain herding, whereas the coefficients of extreme levels of trading volume $\beta_{11}(\beta_{12})$ are negatively related and significant at 1% level (t-statistics: −7.71 and −10.41), indicating evidences of herding behavior by investors during periods of low (high) trading volume.

The effect of open interest and changes in open interest is examined on herding and the results that the coefficient of interest β_{13} is positive and significantly related at 1% significance level (t-statistics: 33.47), providing negative support to herding behavior, while the coefficient of extreme low (negative) and large (positive) $\beta_{14}(\beta_{15})$ are positively related and significant at 1% significant level (t-statistics: 2.92 and 3.46), thus reporting negative evidence to herd behavior.

The results from Panel (G), highlights that including $CSAD_t^S$ and the squared index returns from the spot market has not changed the sign and statistical significance of the coefficients from β_7 to β_{14} except β_{10} and β_{14}. Though there is no change in significance level but relationship changed in sign indicating support for herding, otherwise stock market events neither affects the parametric values of the other variables nor subsume their informational content, which are still found related with significant herding behavior.

However, the coefficient of CSAD of spot market is found positive and statistically significant at 1% significance level (t-statistics: 2969.81), which supports significant spillover effects in terms of herding in different markets at cross country level as evident from (Chiang and Zheng, [16]; Galariotis *et al.* [1]). This indicates that the events in the underlying markets highly influence futures market as evidenced by the positive correlation (0.97) between cross-sectional returns dispersion of spot and futures market. While the coefficient of squared index returns of spot market is found positively related and significant at 1% significance level (t-statistics: 35.59), indicating non-linear relationship.

6. Conclusions

This paper examines the herding behavior of Indian investors in index futures market based on daily data collected from the futures and options (F & O) segment of NSE over the period from January 2011 to June 2016, for testing the herding behavior, using cross-sectional dispersion (CSAD) as a measure developed by Chang *et al.* (2000) for providing investors tendency to follow market consensus conditional upon a set of systematic factors from a list of variables namely from macroeconomic news releases, period of market stress, during extreme trading volume and spillover's from other markets. The test results consistently displayed herding behavior during periods of extremely low (high) trading volume, spillovers from other market segments and during periods of release of macroeconomic news announcements.

The results of the study have significant implications in asset pricing and portfolio management as trading by investors in the direction of the market would limit hedging of risk and impair diversification benefits. In additions, it sends signals for policy makers to create more transparency in the financial markets to reduce informational asymmetry among varied class of participants in the markets to minimize adverse selection problems. Though, herding is noticed in index futures market, this study has not addressed other issues, like herding in other market segments and usage of other theoretical models. In addition, future research should look into aspects of herding by different classes of investors and especially roles of domestic institutional investors (DIIs) and foreign institutional investors (FIIs) in these markets which are part of future studies.

References

[1] Galariotis, E.C., Rong, W. and Spyrou, S.I. (2015) Herding on Fundamental Information: A Comparative Study. *Journal of Banking & Finance*, **50**, 589-598. https://doi.org/10.1016/j.jbankfin.2014.03.014

[2] Nofsinger, J.R. and Sias, R.W. (1999) Herding and Feedback Trading by Institutional and Individual Investors. *The Journal of Finance*, **54**, 2263-2295. https://doi.org/10.1111/0022-1082.00188

[3] Bekaert, G., Ehrmann, M., Fratzscher, F. and Mehl, A. (2012) Global Crises and Equity Market Contagion. Working Paper.

[4] Christie, W.G. and Huang, R.D. (1995) Following the Pied Piper: Do Individual Returns Herd around the Market? *Financial Analysts Journal*, **51**, 31-37. https://doi.org/10.2469/faj.v51.n4.1918

[5] Banerjee, A.V. (1992) A Simple Model of Herd Behavior. *The Quarterly Journal of Economics*, **107**, 797-819. https://doi.org/10.2307/2118364

[6] Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992) A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, **100**, 992-1026. https://doi.org/10.1086/261849

[7] Welch, I. (1992) Sequential Sales, Learning, and Cascades. *Journal of Finance*, **47**, 695-732. https://doi.org/10.1111/j.1540-6261.1992.tb04406.x

[8] Cipriani, M. and Guarino, A. (2007) Transaction Costs and Informational Cascades in Financial Markets: Theory and Experimental Evidence. European Central Bank No. 736, European Central Bank, Frankfurt.

[9] Hwang, S. and Salmon, M. (2004) Market Stress and Herding. *Journal of Empirical Finance*, **11**, 585-616. https://doi.org/10.1016/j.jempfin.2004.04.003

[10] Bikhchandani, S. and Sharma, S. (2000) Herd Behavior in Financial Markets. *IMF Economic Review*, **47**, 279-310.

[11] Hirshleifer, D., Subrahmanyam, A. and Titman, S. (1994) Security Analysis and Trading Patterns When Some Investors Receive Information before Others. *The Journal of Finance*, **49**, 1665-1698. https://doi.org/10.1111/j.1540-6261.1994.tb04777.x

[12] Shiller, R.J., Fischer, S. and Friedman, B.M. (1984) Stock Prices and Social Dynamics. *Brookings Papers on Economic Activity*, **1984**, 457-510. https://doi.org/10.2307/2534436

[13] Hirshleifer, D. and Teoh, S.H. (2003) Limited Attention, Information Disclosure, and Financial Reporting. *Journal of Accounting and Economics*, **36**, 337-386. https://doi.org/10.1016/j.jacceco.2003.10.002

[14] Gleason, K.C., Mathur, I. and Peterson, M.A. (2004) Analysis of Intraday Herding Behavior among the Sector ETFs. *Journal of Empirical Finance*, **11**, 681-694. https://doi.org/10.1016/j.jempfin.2003.06.003

[15] Chang, E.C., Cheng, J.W. and Khorana, A. (2000) An Examination of Herd Beha-

vior in Equity Markets: An International Perspective. *Journal of Banking & Finance*, **24**, 1651-1679. https://doi.org/10.1016/S0378-4266(99)00096-5

[16] Chiang, T.C. and Zheng, D. (2010) An Empirical Analysis of Herd Behavior in Global Stock Markets. *Journal of Banking & Finance*, **34**, 1911-1921. https://doi.org/10.1016/j.jbankfin.2009.12.014

[17] Blasco, N. and Ferreruela, S. (2008) Testing Intentional Herding in Familiar Stocks: An Experiment in an International Context. *The Journal of Behavioral Finance*, **9**, 72-84. https://doi.org/10.1080/15427560802093654

[18] Borensztein, E. and Gelos, R.G. (2003) A Panic-Prone Pack? The Behavior of Emerging Market Mutual Funds. *IMF Staff Papers*, **50**, 43-63.

[19] Zhou, J. and Anderson, R.I. (2011) An Empirical Investigation of Herding Behavior in the US REIT Market. *Journal of Real Estate Finance Economics*, **47**, 83-108. https://doi.org/10.1007/s11146-011-9352-x

[20] Lakonishok, J., Shleifer, A. and Vishny, R.W. (1992) The Impact of Institutional Trading on Stock Prices. *Journal of Financial Economics*, **32**, 23-43. https://doi.org/10.1016/0304-405X(92)90023-Q

[21] Choe, H., Kho, B.C. and Stulz, R.M. (1999) Do Foreign Investors Destabilize Stock Markets? The Korean Experience in 1997. *Journal of Financial Economics*, **54**, 227-264. https://doi.org/10.1016/S0304-405X(99)00037-9

[22] Oehler, A. and Chao, G.G.C. (2000) Institutional Herding in Bond Markets. Working Paper, Bamberg University.

[23] Kim, K.A. and Nofsinger, J.R. (2005) Institutional Herding, Business Groups, and Economic Regimes: Evidence from Japan. *The Journal of Business*, **78**, 213-242. https://doi.org/10.1086/426524

[24] Wylie, S. (2005) Fund Manager Herding: A Test of the Accuracy of Empirical Results Using UK Data. *The Journal of Business*, **78**, 381-403. https://doi.org/10.1086/426529

[25] Demirer, R. and Kutan, A.M. (2006) Does Herding Behavior Exist in Chinese Stock Markets? *Journal of International Financial Markets, Institutions and Money*, **16**, 123-142. https://doi.org/10.1016/j.intfin.2005.01.002

[26] Caporale, G.M., Fotini, E. and Nikolaos, P. (2008) Herding Behavior in Extreme Market Conditions: The Case of the Athens Stock Exchange. *Economic Bulletin*, **7**, 1-13.

[27] Caparrelli, F., D'Arcangelis, A.M. and Cassuto, A. (2004) Herding in the Italian Stock Market: A Case of Behavioral Finance. *The Journal of Behavioral Finance*, **5**, 222-230. https://doi.org/10.1207/s15427579jpfm0504_5

[28] Fu, T. and Lin, M. (2010) Herding in China Equity Market. *International Journal of Economics and Finance*, **2**, 148-156. https://doi.org/10.5539/ijef.v2n2p148

[29] Kremer, S. and Nautz, D. (2013) Causes and Consequences of Short-Term Institutional Herding. *Journal of Banking & Finance*, **37**, 1676-1686. https://doi.org/10.1016/j.jbankfin.2012.12.006

[30] Conrad, J., Gultekin, M.N. and Kaul, G. (1991) Asymmetric Predictability of Conditional Variances. *Review of Financial Studies*, **4**, 597-622. https://doi.org/10.1093/rfs/4.4.597

[31] Bekaert, G. and Wu, G. (2000) Asymmetric Volatility and Risk in Equity Markets. *Review of Financial Studies*, **13**, 1-42. https://doi.org/10.1093/rfs/13.1.1

[32] Boyd, J.H., Hu, J. and Jagannathan, R. (2005) The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks. *The Journal of Finance*, **60**, 649-672. https://doi.org/10.1111/j.1540-6261.2005.00742.x

[33] Savor, P. and Wilson, M. (2013) How Much Do Investors Care about Macroeconomic Risk? Evidence from Scheduled Economic Announcements. *Journal of Financial and Quantitative Analysis*, **48**, 343-375. https://doi.org/10.1017/S002210901300015X

[34] Ederington, L.H. and Lee, J.H. (1993) How Markets Process Information: News Releases and Volatility. *The Journal of Finance*, **48**, 1161-1191. https://doi.org/10.1111/j.1540-6261.1993.tb04750.x

[35] Diamond, D.W. and Verrecchia, R.E. (1991) Disclosure, Liquidity, and the Cost of Capital. *The Journal of Finance*, **46**, 1325-1359. https://doi.org/10.1111/j.1540-6261.1991.tb04620.x

[36] Voronkova, S. and Bohl, M.T. (2005) Institutional Traders' Behavior in an Emerging Stock Market: Empirical Evidence on Polish Pension Fund Investors. *Journal of Business Finance & Accounting*, **32**, 1537-1560. https://doi.org/10.1111/j.0306-686X.2005.00639.x

[37] Girma, P.B. and Mougou, M. (2002) An Empirical Examination of the Relation between Futures Spreads Volatility, Volume, and Open Interest. *Journal of Futures Markets*, **22**, 1083-1102. https://doi.org/10.1002/fut.10047

[38] Donders, M., Kouwenberg, R. and Vorst, T. (2000) Options and Earnings Announcements: An Empirical Study of Volatility, Trading Volume, Open Interest and Liquidity. *European Financial Management*, **6**, 149-171. https://doi.org/10.1111/1468-036X.00118