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Analysis of Sectoral Herding through Quantile Regression: A Study of S&P BSE 500 Stocks

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Abstract

The current study empirically investigates sector-wide flock activity for the S&P BSE 500 stocks over 8 years spanning from October 2010 till September 2018. Drawing on absolute deviation model by Chang et al. (2000), the present analysis tends to unravel the curvilinear relationship between consensus return and dispersion via Ordinary Least Squares and Quantile Regression approaches. Using conventional regression, a nonexistent herd hunch is inferred under both normal and asymmetric scenarios. However, the examination of distribution tails discovers herding in auto and engineering sector during bull markets and healthcare sector during bearish conditions. However, the two crises namely the oil crisis of 2014 and the Chinese crash of 2015 subject the Indian bourse to mimicking behavior. This may be a matter of concern for the policy makers as the evidences reflect on the unstable nature of the S&P BSE 500 index and the Indian stock market as a whole. Therefore, the regulatory bodies have to make consistent efforts to bridge the informational distance between various classes of investors and corporate houses to ensure more transparent and honest practices so that investors can make informed and better decisions. Finally, the investors may resort to active trading rules during turbulence to earn more than what market warrants.

Key words: Herding; Ordinary Least Squares; Quantile Regression; Indian Stock Market

JEL classification: C3; C31; G1; G4; G41

1. Introduction

Financial literature posited a balanced state of risk and return whereby sophisticated market participants would behave wisely. The markets were portrayed efficient that facilitated hassle free transmission of information and ensured

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homogeneity in expectations of all market players. Further, the financial assets would always show an arbitrary fundamental value and all the unwarranted and fictitious premiums, if any would be capitalized on without disturbing the mechanics of the financial system (Shrotryia and Kalra, 2019). This whole process would continue until the markets restored an equilibrium state bereft of commotion (Shrotryia and Kalra, 2020). Such a utopian state of equilibrium connoted that markets would break even and the participating agents would get a normal return (Shrotryia and Kalra, 2019). All these traditional arguments failed to recognize noise in the capital markets which btriggered eccentric movements outside the ambit of niche traditional literature (Shrotryia and Kalra, 2018). Consequently, researchers began to see beyond the restricted rational perspective and accepted the inter linkages of finance with various other disciplines especially psychology and behavior (Kumar and Goyal, 2015). They also challenged the quantification and objectivity of drivers of financial decision making and brought about a few non-financial aspects of less than rational but feasible decision making. With this, studies in the area of behavioral finance grew tremendously exemplifying the need and relevance of identification of hidden constructs of the mainstream theories of finance. Such a paradigm embraces the realistic view of decision making whereby decision makers may act either regressively or optimistically but precisely owing to certain inexplicable factors. Also, the assets values do not always align with the discounted value of the projected inflows. All this manifests that rationality is a myth and informational efficiency is a distant dream.

The literature on behavioral finance is vast and entails application of psychology in the areas of private as well as personal finance. On one side, this dimension deals with certain psychological impediments, commonly known as biases in individual financial decision making. On a relatively larger scale, it approves of the existence of anomalous market waves and other absurd subtleties (Pompian, 2006). This macro aspect accepts the proposition of memory in the asset prices and their even trends. The present study tends to unravel the behavioral inclinations shaping the character of the capital markets. These subjective influences are a mix of mood, fear, anxiety, apprehension, optimism, pessimism, etc. to mediate responses to some external stimuli. Such idiosyncrasies can be innate to an individual or absorbed from the external environs which make decision makers knowingly or unknowingly resort to a cognitive refuge (or bias) to escape inexplicable situations (Shrotryia and Kalra, 2020). One such interesting and crucial bias is herding, which implies nothing but a behavioral mindset to walk in sync with the crowd. In other words, it would suggest synergistic economic moves of major players especially investors in the capital markets (Gabbori *et al.,* 2020). In a highly unpredictable financial environment, such an escape is often resorted to by the financial decision makers. Consequently, they may not certainly assess the financial securities based on their credentials. One plausible cause of this factor is uncertainty or fear about unforeseen events. Such emotional imbalances drive investors to rely on the signals by other participants and correlate their forthcoming actions. Further, such a propensity to aggregate trade in a particular class of the asset may prove pernicious to the financial health of an emerging market like India for it may lack sufficient liquidity and transparency.

Therefore, this study seeks to bring about various facets related to sectoral herding in the Indian context using a novel Quantile Regression (QR hereafter) method. Unlike earlier econometric techniques, QR examines clustering of observations (returns) in the tails of distribution especially when the stock markets torment.

This research paper is further categorized as; Section 2 reviews the relevant literature. Section 3 provides objectives of the present study. Section 4 describes the data and methodology. Section 5 manifests the empirical results. The last section concludes this empirical study.

2. Literature Review

In financial terminology, herding refers to a market-wide phenomenon whereby every single participant copies the actions of every other market participant (Shrotryia and Kalra, 2020). In other words, it suggests collective economic interaction of all the agents with the dynamics of capital markets either out of will or by virtue of sharing identical information set and trading environment. Also, investors may over rely on the inferences from the acts of others and end up overlooking their own trading signals to avoid any substantial monetary loss (Bohl *et al.,* 2017). According to Devenow and Welch (1996), such skepticism about one’s informational strength and quality weaves a web of cascades and spillovers to dislocate the standard state of equilibrium. Further, Clements et al. (2017) call this behavior a strategic and prudent move to safeguard one’s goodwill among peers whereas Spyrou (2013) ascribe it to the psychological distortions and illusions. Such an illusion of being safe with the masses emanates skewed trading patterns and excess volatility (Gebka and Wohar, 2013). These implications have been quantified and investigated using various measures proposed by academicians which are further categorized as volume based and return based. The former considers the quantum of assets traded (or transaction) as a surrogate for coordinated financial behavior (Lakonishok *et al.,* 1992; Sias, 2004; Wermers, 1999, among others) whereas the capital asset returns have been the essence of the latter technique (Chang *et al.,* 2000; Christie and Huang, 1995, among others). Both the aforesaid methods have been used in international markets. For instance, Venezia et al. (2011) employed the technique by Lakonishok et al. (1992) to reveal strong herding propensity among stocks of smaller companies by less informed and naïve market participants. Using similar model, Holmes et al. (2013) discovered that institutions moved in tandem with each other by virtue of sharing similar information in a less fragmented market like Portugal. Blake et al. (2017) applied Sias (2004) and Choi and Sias (2009) empirical method on monthly data of 189 UK based pension funds and revealed strong convergent purchase and sale of financial assets.

Similarly, the other set of measures focus primarily on the asset returns and examine dispersion between the market and individual asset return as an indication of herding. These asset specific methods were first proposed by Christie and Huang (1995) and Chang et al. (2000) and have been largely applied to investigate market-based flock hunch in less liquid stock markets (Demirer and Kutan, 2006; Javaira and Hassan, 2015; Yao *et al.,* 2014, among others). These methods have even been extended to examine lemming instinct in sector specific financial assets (Gebka and Wohar, 2013; Litimi, 2017). However, the volume centric methods have been most popular with advanced capital markets as such markets may provide reasonable liquidity to the participants to unwind their market position rapidly and conveniently. Further, these methods are considered better as they manifest the direction (buy or sell) of the transaction to help fund managers understand which side is risking the market more.

Moving ahead, the academicians are now exploring the flock movement by delving into the behavior of asset returns' deviation in the tails of the distribution owing to various reasons. Firstly, the Ordinary Least Squares (OLS hereafter) method's estimates are sensitive to the extreme and asymmetric values. Secondly, the results may over emphasize mean or average while modeling the relation between the relevant variables. Therefore, the current study uses QR, which seeks to test flock mentality in various quantiles of the distribution by walling off the possible results' distortion by outliers. Also, every quantile is examined as a subset of overall observations than separately. This novel regression approach unfolds many latent yet crucial findings in the overall examination of herding in various international markets. For instance, Chiang et al. (2010) use QR to reveal new evidences of imitative economic actions for Chinese B stocks especially when market upsurges. Similarly, herding is demonstrated for various quantiles during crisis against its insignificant estimates using conventional regression (Bekiroz *et al.*, 2017). Economou et al. (2016) detect herd hunch for daily data observations in higher quantiles characterized by greater degree of uncertainty. Further, Chaffai and Medhioub (2018) conclude nonexistent market herding during downfall in some regionally integrated economies of the Middle East.

Further, the Indian literature is deficient with only a handful exploring convergent financial behavior for the whole market. For instance, Lao and Singh (2011) investigate the lemming activity for 100 blue-chip companies listed on BSE. Lakshman et al. (2013) highlight the impact of foreign investors' trading strategies on herding level in domestic market. Shrotryia and Kalra (2019) examine the components of S&P BSE Sensex and conclude no herd trading in the Indian market. Therefore, lack of empirical examination of herding in sectoral assets is the primary motivation of the current study. Also, of a few attempts made to examine the distribution tails to reveal herd (or anti-herd behavior), none concerns the Indian stock market. Therefore, this study proposes to use both traditional OLS and a more robust QR technique to study herding foible across major sectors of S&P BSE 500 stocks.

3. Motivation and Objectives

Herding has long been accused of roping many market participants in to deflect from the consistent and systematic way of thinking and make sub-standard choices. Besides providing temporary answers to various complexities, it often results into a vicious loop of upsurges and ensuing fiscal meltdowns. Therefore, a detailed empirical investigation into the intensity and forms of herding is important as it will help market regulators to take measures (both preventive and corrective) for market stability. Considering this, the current research study proposes:

- To gauge sectoral herding in the Indian stock market for the whole sample period;
- To gauge sectoral herding in the Indian stock market during asymmetries; and
- To examine the sectoral herding in the Indian stock market during crises.

On the basis of the aforementioned research objectives, the study posits four main hypotheses for each of the 8 sectors. The sector specific hypotheses are as follows:

Null Hypothesis H_0^1:	"There is no significant sector-wide herd activity in the Indian stock market for whole observations."
Null Hypothesis H_0^2:	"There is no significant sector-wide herd activity in the Indian stock market for the up and down market scenarios (or asymmetries)."
Null Hypothesis H_0^3:	"There is no significant sector-wide herd activity in the Indian stock market during the oil crisis of 2014."
Null Hypothesis H_0^4:	"There is no significant sector-wide herd activity in the Indian stock market during the Chinese crisis of 2015."

4. Data, Market Description and Methodology

4.1 Data Description

The dataset entails daily and weekly stock prices of S&P BSE 500 companies from October 2010 till September 2018 (8 years). All the data have been sourced from Prowess database maintained by Centre for Monitoring Indian Economy (CMIE). Initially the sample had 342 companies without any missing data over the sample period. These companies were further classified into 11 sectors according to Value Research Classification. The second stage of data filtration excluded sectors with less than 10 stocks and combined some sectors to ensure even distribution of companies under each head. Table 1 gives the representation of final 332 companies classified into 8 sectors. Using an excel function (*LN*), return on individual stock ($R_{s,t}$) is calculated as the logarithmic difference between close price at time *t* ($P_{s,t}$)and at time *t*-1 ($P_{s,t-1}$).

4.2 Indian Stock Market

Indian stock market is one of the fastest growing emerging markets in the Asian region, offering reasonable liquidity to the market participants to complete a financial transaction. It operates via multiple stock exchanges, of which, two popular ones are Bombay Stock Exchange (BSE; 1875) and National Stock Exchange (NSE; 1992). The present study uses one of the broad-based benchmark indices of BSE i.e., S&P BSE 500 to study the herd bias in the Indian stock market. Such an index was established in the year 1999 with an aim to capture the performance of the top 500 companies listed on the BSE spreading across 22 major sectors of the Indian economy. In other way, it acts as a barometer of the Indian stock market and its movements. Further, the Indian market has been found to be inefficient in weak form (Ahmad *et al.,* 2006). In other words, the market may not be restricted to normal profit and permit the participants to exploit the mispricing to earn abnormal returns. Consequently, the investors may resort to psychological shortcuts or biases while making financial decisions, challenging the traditional assumptions. Therefore, it seems appropriate to gauge the sectoral herding tendencies in the Indian bourse.

4.3 Methodology

The presence of sector-wide flock behavior is tested using cross-sectional absolute deviation (CSAD) model developed by Chang et al. (2000). This is an improvement over the cross-sectional standard deviation (CSSD) approach of Christie and Huang (1995) as it explores convergent economic behavior in both normal and skewed investment environment. Also, CSAD model walls off the issue of extreme values. However, both Christie and Huang (1995) and Chang et al. (2000) posit that the difference between return on individual security and the market portfolio keeps on decreasing when investors follow the trading signals of throng. CSAD is calculated as:

$$CSAD_t = \frac{1}{N}\sum_{s=1}^{N}\left|R_{s,t} - R_{m,t}\right| \tag{1}$$

where, $CSAD_t$ = cross-sectional absolute deviation, $R_{s,t}$ = return on stock *s* of a particular sector under study, and $R_{m,t}$ = equally weighted return of *N* stocks in each sector portfolio (or consensus return for each sector). All these variables are determined at time *t*.

Further, Chang et al. (2000) challenges the traditional CAPM notion by taking CSAD or dispersion to be a non-linear function of consensus return (or return on the market portfolio). This non linearity is stated as:

$$CSAD_t = \alpha + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \varepsilon_t \tag{2}$$

where, $\left|R_{m,t}\right|$ manifests the absolute value of consensus return, $R_{m,t}^2$ represents the squared value of consensus return, and ε_t shows an error term. All the aforesaid parameters are specified for time *t*. Also, α denotes a constant value (or an intercept) even when all the regressors turn zero. A separate time series regression is run for all the sectors. A significant and negative coefficient β_2 shows herd behavior for each sector. Also, for the skewed conditions of the stock market, a dummy (d) has been used in the below mentioned equation. It examines whether asymmetric situations intensify lemming instinct as reflected in convergence of market and individual returns.

$$CSAD_t = \alpha + (1-d)\beta_1 \ |R_{m,t}| + d\beta_2 \ |R_{m,t}| + (1-d)\beta_3 \ R_{m,t}^2 + d\beta_4 \ R_{m,t}^2 \ + \varepsilon_t \qquad (3)$$

where, dummy (d) assumes unity when the market declines ($R_{m,t}$< 0) and zero when the market rises ($R_{m,t}$> 0). The negative and significant values of β_3 and β_4 suggest herd instinct during rising and falling markets, respectively.

It is often argued that herding bias intensifies during periods of excessive volatility (Christie and Huang, 1995). Therefore, the present study gauges the presence and extent of herding behavioral bias in the wake of two of the major crises namely the oil crisis of 2014 and the Chinese crash of 2015. The two crises are crucial to examine as the first involves a stark fall in the crude oil prices impacting the exports and imports of crude oil, whereas in the latter case, the major Shanghai stock indices lost more than half of their market values impacting the domestic and foreign investments (Shrotryia and Kalra, 2020).

Equation (4) represent the dummy regressions model examining the existence of herding behavior in the turbulent periods or crises.

$$CSAD_t = \alpha + \ \beta_1|R_{m,t}| + \ \beta_2 R_{m,t}^2 + d_o\beta_3 R_{m,t}^2 + \ \varepsilon_t \qquad (4)$$

A separate dummy regression is run for both the crises. In case of oil crisis, dummy (d_o) assumes one during the period spanning from June, 2014 till March, 2015 and zero otherwise whereas (d_o) takes one during the period spanning from June, 2015 till August, 2016 and zero otherwise in case of the Chinese crash (Shrotryia and Kalra, 2020). The negative and significant value of β_3 suggests robust herd behavior during each crisis.

Equations (2), (3) and (4) are the OLS regressions for normal, asymmetric market and crises scenarios, respectively. However, this analysis is incomplete as it fails to capture the behavior of observations in the tails of the return dispersion distribution for each sector. Therefore, this empirical study also applies QR to discover the unidentified market fallacy in the tails (or ends) of the distribution of the dependent variable, if any. Equation (2) is reframed as:

$$Q_\tau(\tau/Y_t) = \ \alpha_\tau + \ \beta_{1,\tau}|R_{m,t}| + \ \beta_{2,\tau}R_{m,t}^2 + \ \varepsilon_{t,\tau} \qquad (5)$$

where, Y_t signifies the vector of regressors mentioned on the right-hand side of the aforementioned equation. A separate time series econometric model is run for each sector. A significant and negative coefficient ($\beta_{2,\tau}$) manifests sector-wide flock behavior for quantile τ. Similarly, equation (3) is reformulated as:

$$Q_\tau(\tau/Y_t) = \alpha_\tau + (1-d)\beta_{1,\tau} \ |R_{m,t}| + d\beta_{2,\tau} \ |R_{m,t}| + (1-d)\beta_{3,\tau} \ R_{m,t}^2 + d\beta_{4,\tau} + \varepsilon_{t,\tau} \qquad (6)$$

where, $\beta_{3,\tau}$ and $\beta_{4,\tau}$ are the quantile specific sectoral herding indicators for up and down phases, respectively. Finally, equation (4) is reformulated as:

$$Q_\tau(\tau/Y_t) = \alpha_\tau + \beta_{1,\tau} \left|R_{m,t}\right| + \beta_{2,\tau} R_{m,t}^2 + d_o\beta_{3,\tau} R_{m,t}^2 + \varepsilon_{t,\tau} \quad (7)$$

where, $\beta_{3,\tau}$ is the quantile specific sectoral herding indicator for the crisis periods. In consultation with Chiang et al. (2010) and Pochea et al. (2017), the quantiles are determined at 10%, 25%, 50%, 75% and 90%. All the econometric modeling has been done using E-views 9.

5. Results

5.1 Descriptive Statistics

Table 1 gives a snapshot of some crucial univariate statistics of the main series, namely, $R_{m,t}$ and CSAD for daily and weekly data points in panel (A) and (B), respectively. The results of Dickey and Fuller (1979)'s test indicate absence of unit root in both $R_{m,t}$ and CSAD. Also, the main variables of this study are not normally distributed as per Jarque-Bera statistic. However, the results for the same are not mentioned for brevity. Sectors like consumer durables and healthcare have the highest mean market return $(R_{m,t})$ whereas services sector shows highest average CSAD for both data frequencies. Further, the standard deviation for weekly data is considerably higher than that of daily data observations across all sectors.

Table1. Descriptive Statistics of $R_{m,t}$ and $CSAD_t$

Sectors	No. of firms	Variables	Daily (A)			Weekly (B)		
			ADF	Mean	SD	ADF	Mean	SD
A&E	44	$R_{m,t}$	-36.41***	0.00	0.01	-18.02***	0.00	0.03
		$CSAD_t$	-12.88***	0.01	0.00	-9.70***	0.03	0.01
C&M	50	$R_{m,t}$	-36.62***	0.00	0.01	-19.17***	0.00	0.03
		$CSAD_t$	-9.37***	0.02	0.00	-7.72***	0.03	0.01
C&R	33	$R_{m,t}$	-36.99***	0.00	0.01	-17.22***	0.00	0.03
		$CSAD_t$	-13.06***	0.02	0.01	-15.61***	0.03	0.01
C&FMCG	43	$R_{m,t}$	-36.03***	0.00	0.01	-17.82***	0.00	0.02
		$CSAD_t$	-12.50***	0.01	0.00	-9.99***	0.03	0.01
Energy	26	$R_{m,t}$	-38.42***	0.00	0.01	-19.46***	0.00	0.03
		$CSAD_t$	-15.38***	0.01	0.00	-16.41***	0.03	0.01
Financial	59	$R_{m,t}$	-38.27***	0.00	0.01	-18.37***	0.00	0.03
		$CSAD_t$	-17.26***	0.01	0.00	-15.31***	0.03	0.01
Healthcare	28	$R_{m,t}$	-36.53***	0.00	0.01	-18.97***	0.00	0.02
		$CSAD_t$	-11.07***	0.01	0.00	-10.53***	0.03	0.01
Services	49	$R_{m,t}$	-37.55***	0.00	0.01	-18.25***	0.00	0.03
		$CSAD_t$	-14.30***	0.02	0.00	-15.03***	0.04	0.08

Note: ADF and SD denote Augmented Dickey Fuller test given by Dickey and Fuller (1979) and standard Deviation, respectively. ***, ** and * define statistical significance at 1%, 5% and 10%, respectively. Source: Authors' creation.

5.2 Herding Results

Table 2 shows the regression results of equations (2), (3), (4), (5), (6) and (7) with OLS and QR estimates. The table enlists only the relevant coefficients (panel (A): β_2 for Eq 2&5; panel (B): β_3 for Eq 4&7 (oil crisis); panel (C): β_3 for Eq 4&7 (Chinese crisis); panel (D): β_3 &β_4 for Eq 3&6) the purpose of brevity. The table only reports coefficient values and not t-statistics. Equation (2) estimates in panel (A) reveal that herding is absent as the relevant coefficient as per OLS is positive and significant in maximum cases. This phenomenon is often known as an anti or reverse herd behavior characterized by divergence from crowd or consensus (Bekiroz *et al.*, 2017). Such deviation from group behavior partially suggests that the Indian stock market investors apply their judgment while making an investment decision. Moving ahead, the highest value of anti-herd coefficient is documented in daily observations of financial (β_2 = 2.78) and weekly observations of services sector (β_2 =3.75). Similar results of anti-herding are obtained using QR model. Considering high frequency daily data, the reverse herding is more pronounced for lower quantiles (τ =10% and τ =25%) than median (τ=50%) and higher quantiles (τ =75% and τ = 90%) in sectors like auto and engineering, consumer durables, and healthcare. However, weekly set of observations discover strong anti-herd propensity for most sectors in all quantiles (lower, middle and upper). The exceptions are chemicals and metals, financial, and healthcare with insignificant herding (or anti-herding) parameters. The overall results for the whole sample of observations bring about a strong deflection from the throng decision, which is also manifested by the widening gap between $R_{s,t}$ and$R_{m,t}$. As a result, the first null hypothesis (H_0^1) is supported in all the cases.

Panel (D) represents the results of equations (3) and (6) for downward and upward market scenarios using OLS and QR.

Table 2. Results of Herding Equations (2), (3), (4), (5), (6) & (7)

S	Model	Eq 2 & 5 (A)		Eq 4 &7 (oil crisis) (B)		Eq 4 &7 (Chinese crisis) (C)		Eq 3 & 6 (asymmetric phases) (D)			
		D	W	D	W	D	W	D		W	
		β_2	β_2	β_3	β_3	β_3	β_3	β_3	β_4	β_3	β_4
A&E	OLS	0.35	2.45***	2.44***	0.62	-1.46**	-1.92*	0.46	0.93**	2.27***	2.87***
	τ= 10%	0.76*	3.54***	1.72***	0.16	-0.98*	-1.94	-2.39*	1.14***	3.40***	4.14***
	τ= 25%	0.36*	3.03***	1.27**	0.02	-0.61	-1.64	-0.07	0.72***	3.05***	3.38***
	τ= 50%	0.20	1.94***	4.31***	0.89	-2.83**	-1.92*	1.67	0.64**	1.98***	2.57***
	τ= 75%	0.91	2.06***	4.56*	0.25	-3.14**	-1.72**	3.01***	3.74	1.72***	1.56*
	τ= 90%	2.07	1.63***	5.89	1.02	-3.42***	-1.43***	1.50*	0.71	1.40**	4.52***
C&M	OLS	0.92**	1.54***	0.64	0.41	-0.20	-0.51	1.96**	1.63***	1.38***	1.94***
	τ= 10%	1.53**	1.10	0.98***	0.74**	0.28	-0.56***	2.20	1.80***	1.82***	0.81
	τ= 25%	1.18***	1.71***	0.76	0.24	-0.45	-0.70***	0.01	1.50***	1.65***	2.25***
	τ= 50%	0.65***	1.45***	0.12	0.34	-0.36	-0.45	1.13	1.62	1.46***	2.10**
	τ= 75%	0.15	1.56	0.36	0.22	0.02	-0.04	2.81*	1.62*	1.14	2.32**
	τ= 90%	0.59	1.46	3.98	1.45	0.80	-0.49	3.77	0.64***	3.98	2.05
C&R	OLS	2.47*	2.98***	0.98	-0.68	-2.23***	-1.26	3.50***	2.48***	2.57***	3.78***
	τ= 10%	1.95*	3.04***	0.37	-0.59	-0.72***	-0.64	3.34	2.44***	2.55***	3.09***
	τ= 25%	2.03*	2.88***	2.05***	-1.04**	-1.28*	-0.76	2.40*	2.42***	2.43*	3.53***
	τ= 50%	2.60	2.17**	2.10*	-0.95	-2.08**	-0.90*	2.54	3.39	2.53***	2.42***
	τ= 75%	4.68*	2.55**	2.08	0.57	-3.11***	-1.97*	3.72***	4.68*	2.12***	2.87
	τ= 90%	5.45	3.91***	0.49	0.42	-3.81**	2.68***	4.05	8.58**	1.65***	3.78***
C & FMCG	OLS	1.74*	3.17***	0.94	1.52***	-2.22***	-1.06	7.57***	2.41***	2.66**	3.31***
	τ= 10%	2.40*	4.93***	0.28	0.37	-1.03	-1.22	6.05***	2.79***	0.65	4.83
	τ= 25%	1.94*	3.91**	0.67	0.77	-0.84	-1.58	6.80***	2.45***	3.67*	4.75***
	τ= 50%	2.10	3.05**	1.08	1.89	-2.46***	-0.99	7.34***	2.01***	2.07	2.38
	τ= 75%	2.02	3.43***	1.74	2.30	-3.97**	-0.64	5.74*	3.01	3.43***	3.31**
	τ= 90%	1.33	3.55***	5.66	0.80	-2.37*	-0.88*	5.12	2.04	2.66***	3.73***
Energy	OLS	0.95**	1.65***	-7.23***	-0.67	0.09	-0.12	0.04	1.48***	1.49***	2.15***
	τ= 10%	1.86***	2.50***	2.27	-0.59	-0.11	-1.50***	1.96***	1.86***	2.49***	2.15
	τ= 25%	1.47***	1.97***	1.05	-0.51	0.39	-0.73	1.07***	1.65***	1.24	1.93*
	τ= 50%	0.90***	1.82***	3.24	-0.72**	0.76	0.14	0.15	1.41***	1.86***	2.48***
	τ= 75%	0.55**	1.47***	2.06	-1.03**	-0.21	1.83	-0.47	2.51	1.49***	1.93***
	τ= 90%	0.50	1.38***	-6.08	-0.61	-2.63	0.96	-1.08	2.53	0.53	1.56***
Financial	OLS	2.78***	2.09***	-1.78*	0.29	-1.50***	-0.56	7.09***	1.76***	2.1***	2.00***
	τ= 10%	1.46***	1.68	-0.42	0.34	-0.64	0.37	0.89	1.76***	2.52***	0.72
	τ= 25%	1.08***	2.19***	-0.58	0.47	-0.92***	0.04	2.15**	1.34***	2.41***	2.04***
	τ= 50%	1.74	2.16***	0.65	0.14	-1.50***	-0.44	2.53***	1.00***	1.95***	2.41***

	τ= 75%	2.44*	2.33**	-0.26	-0.31	-1.20	-1.12*	4.17***	3.11**	2.27	1.84**
	τ= 90%	6.84	3.41***	-2.99	-0.20	-4.28***	-1.80***	8.56***	3.62	4.03***	2.74**
Healthcare	OLS	0.98*	0.71	2.60**	1.38	-0.92	0.18	6.34***	1.78***	1.18	0.96
	τ= 10%	1.45***	-1.69	1.80*	1.38	-1.32	-1.31	8.65***	2.41***	0.87	-1.76
	τ= 25%	1.01***	1.61	-0.14	-0.82	-1.80*	0.72	5.13***	1.70***	0.60	1.86
	τ= 50%	1.07	2.10**	1.57	1.61	-1.14	-0.50	5.11*	1.34	5.52***	2.77***
	τ= 75%	0.35	0.86	6.02	1.97	-0.54	0.79	5.30*	1.03	1.67	2.10
	τ= 90%	2.72	-1.98	6.07**	0.49	-1.65	0.04	7.86*	2.83	-1.33	-2.74*
Services	OLS	1.04**	3.75***	1.27	0.44	-1.43**	-1.79***	2.12	1.38***	4.26***	3.49***
	τ= 10%	1.92***	2.71***	1.47	1.14	-0.89	0.65	2.24	2.01	-1.81	2.51***
	τ= 25%	1.39***	1.79*	1.22*	1.23*	-1.82**	-1.19*	3.40**	1.66***	1.58	3.27*
	τ= 50%	0.86***	4.11**	1.03	0.51	-2.04*	-1.82***	1.45	1.17***	4.92	4.17***
	τ= 75%	0.94	5.37***	1.98	-0.58	-1.24***	-2.34***	2.67**	1.80	4.77***	5.31***
	τ= 90%	-0.35	3.80***	2.38	3.95	-1.14	-3.49***	0.25	0.17	3.44***	2.78

Note: S, A&E, C&M, C&R, C&FMCG, D and W stand for Sectors, Auto & Engineering, Chemicals & Metals, Construction & Real Estate, Consumer Durables & FMCG, Daily and Weekly, respectively. ***, ** and * denote statistical significance at 1%, 5% and 10% respectively. Source: Authors' creation.

The purpose here is to see the investors' inclination to converge (or diverge) in periods of stress as well as boom. OLS values suggest unwillingness on part of market participants to correlate their economic moves. This divergence is significant for most cases. Based on daily data points, the estimation output for the lowest quantile (τ=10%) discovers robust herd hunch in auto and engineering sector for bull phases (β_3 = -2.39). Based on weekly observations, the highest quantile (τ = 90%) also depicts a significant evidence of behavioral convergence for healthcare sector in bearish situations (β_4 = -2.74). Moving forth, the remaining cases show either nonexistent herding or strong anti-herd propensity. This may also suggest that informational divide is more pronounced in sectors like auto and engineering and healthcare. Therefore, the second null hypothesis (H_0^2) is supported in all cases except auto and engineering (for daily data during up market) and healthcare sector (for weekly data during down market), when QR is applied.

Moving ahead, panels (B) and (C) represent the herding results for the oil and the Chinese crises, respectively. In panel (B), using OLS, a strong herd hunch is found for daily observations of the energy (β_3 = -7.23) and financial (β_3 = -1.78) sectors. For weekly data, QR technique seems more robust to detect herding in the construction and real estate (τ = 25%) and energy (τ= 50% and 75%) sectors.

Further, the Chinese crash of 2015 appears to strongly stimulate herding bias in the Indian stock market (panel (C)). It is observed that construction and real estate sector has all significant herding coefficients using both OLS and QR. Whereas, auto and engineering, consumer durable and FMCG, financial and services sectors are affected in most cases. However, chemicals and metals, energy and healthcare are a few sectors with minimal or no impact of the Chinese crisis. When tested using weekly data, herding is documented for all the sectors except healthcare.

The overall results reveal insubstantial sector-wide correlated behavior during normal and asymmetric periods in the Indian stock market. Further, the crises (both oil crisis and the Chinese crisis) subject the Indian bourse to herding bias. Also, the study approves of the supremacy of QR in explaining the undiscovered financial mirage (Pochea *et al.,* 2017). For instance, panel (A) shows that the herding coefficient turns positively substantial for lower quantiles (τ = 10% and 25%) against its insignificant OLS estimate for daily data of auto and engineering sector. Considering weekly data series, another noteworthy point is that chemicals and metals exhibit a significant anti-herd behavior for lower (τ = 25%) and median (τ = 50%) quantiles whereas the relevant coefficients become insignificant for higher quantiles. Likewise, using weekly data observations, a robust anti-herd activity is documented in the median quantile (τ = 50%) for healthcare sector against no significant estimate of conventional least squares regression.

As per panel (D), using OLS, weekly observations of healthcare sector bring an insignificant and unobservable relevant parameter against a significantly negative coefficient in the highest quantile (τ = 90%) when the financial market plummets. Similarly, an unidentified herd hunch is captured at the lowest quantile (τ =10%) for daily observations of auto and engineering sector in the rising market situations. Such herding in two of the defensive sectors (auto and engineering and healthcare) defines the risk-averse behavior of the Indian investors during volatile periods characterized by frequent fluctuations. Finally, QR seems effective in bringing out an otherwise unidentified lemming like activity in panel (C) for weekly observations of chemical and metals (τ = 10% and 25%) and energy (τ = 10%) sectors while for daily observations of healthcare sector (τ = 25%). This manifests that a particular set or quantile of observations depict herd activity, which is likely to get offset by the impact of the other sets of observations in OLS.

6. Discussion and Conclusion

6.1 Discussion

The present study seeks to bring out multiple facets associated with one of the biggest market fallacies i.e., herding in the major sectors of S&P BSE 500 from October 2010 till September 2018. Similar sectoral studies have been carried out in other Asian markets (Lee *et al.*, 2013; Vo and Phan, 2017; Zheng *et al.*, 2017, among others). Using OLS, a nonexistent flock hunch is inferred under both normal and asymmetric scenarios. Instead, a reverse herd activity is observed whereby the market participants rely on their own informational signals and therefore flinch away from the consensus. Such negative herding is also witnessed in the Australian market for intraday data points (Henker *et al.,* 2006). Also, Lam and Qiao (2015) reveal increased dispersion of returns for sectors like industrial, real estate and hospitality in the Hong Kong stock market. However, the sector-based findings are incongruent to those discovered in the European (Filip *et al.*, 2015), US (Litimi *et al.,* 2016) and the gulf markets (Medhioub and Chaffai, 2019). Moving ahead, the present results discover substantial herding bias during crises periods especially the Chinese crisis of 2015. Similar evidences are documented by Clements *et al.* (2017) and Shrotryia and Kalra (2020) for the US and Indian bourses, respectively. However, this is incongruent to the findings of Shrotryia and Kalra (2019), who conclude that the Indian stock market is free from herd hunch during crisis period.

Further, the study employs an augmented QR approach which fits better in the Indian context as distributions of the main variables in the present study are not normal. The overall results manifest reverse herd activity for whole and skewed market patterns. Further, the present study supports the association of herd behavior with periods of market stress or turbulence. Similar studies have been conducted internationally. For instance, Stavroyiannis and Babalos (2017) highlight statistically substantial reverse herd activity for stocks of ethical companies in the US. However, flock instinct is observed for both Shenzhen and Shanghai stock exchanges (Chen *et al.,* 2017). Also, Pochea et al. (2017) document noticeable market-wide imitative behavior for all quantiles in the Polish stock market.

Since the data observations employed in the aforementioned technique depend upon a particular quantile while estimating the regression parameters, it helps scrutinize distribution tails to locate an otherwise unidentified pattern. For instance, the QR model gives a negatively significant relevant coefficient for auto and engineering (daily data) and healthcare (weekly data) sectors during bullish and bearish phases, respectively. Therefore, it may be said that QR model enhances the explanatory power by exploring the returns' clustering around market for every quantile so that their impact is not offset by the returns' behavior in the overall distribution.

6.2 Conclusion

This empirical study adds to the existing yet deficient literature in two ways. Firstly, it determines the presence of lemming activity for high frequency data across 8 sectors that cover whole or substantially whole of the market share. Another contribution of this research paper lies in the application of both conventional (OLS) and unconventional regression (QR) to investigate this cognitive mediator of an investment decision making. The empirical results for both techniques refute the claims of coordinated trading stances in the Indian stock market especially during normal and skewed periods. However, the two crises namely the oil crisis of 2014 and the Chinese crash of 2015 subject the Indian bourse to mimicking behavior. This may be a matter of concern for the policy makers as the evidences reflect on the unstable nature of the S&P BSE 500 index and the Indian stock market as a whole. Therefore, the regulatory bodies have to make consistent efforts to bridge the informational distance between various classes of investors. Another policy implication for the corporate houses is that they have to ensure more transparent and honest practices so that investors can make informed and better decisions. Finally, the investors may resort to active trading rules during turbulence to earn more than what market warrants.

An extension of this research could be to examine herding foible in many other homogenous sets based on size and value for a relatively longer duration. Also, the current evidences may suffer from the problem of serial correlation and multi collinearity between variables. Therefore, an improved model may be employed in future to eradicate such problems in the time series regression (Yao *et al.,* 2014).

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