EXPLORING BEHAVIORAL BIASES IN STOCK MARKET: EVIDENCE FROM INDIA

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Abstract

Due to the positive association between investments and the development of the economy, the rise of investment will progressively influence the economy's overall growth and vice versa. Thus, investors' decisions play a significant role in describing the market trend, which in turn affects the economy. Individuals invest with unique planning or no planning at all based on their available funds, time span, and financial goal. Ultimately, the majority of them want high returns that will make them wealthy overnight Regardless of how strong the company fundamentals are, strong negative emotions can wreck down a robust bullish market trend. The investor behavior is guided by many factors, such as investment horizons, other investors' actions, risk capacity, personality, and level of volatility in equity markets. Past studies have highlighted that individuals commit various behavioral anomalies due to incomplete information, shortage of technical skills, and belief in their competencies to invest while investing. This study has empirically tried to determine the presence of the predominant behavioral anomalies; the herding bias, overconfidence bias, disposition effect, and noise trading in the Indian stock market. Herding has been tested using the cross-sectional absolute deviation methodology as described by Chang et al. (2000). The other biases have been tested using a time-series regression model, such as VAR and Granger causality. Our sample consists of Nifty 50 companies for 21 years (January, 2000-December, 2020). The research shows that Indian stock markets are efficient as we fail to validate the herding bias for the overall market. However, herd mentality exists in crisis and extreme market conditions. The results also validate the existence of anomalies, such as the disposition effect, overconfidence, and noise trading in the Indian stock market.

KEYWORDS- Inclusive Leadership, Thriving At Work, Innovative Work Behavior, Hospitality Employees

JEL Classification- G1,G4,G5

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1. INTRODUCTION

Mackay(1841) highlighted the incident of Dutch Tulip bubble to demonstrate the erratic behavior of crowd. During the Dutch Golden era, a flower named as *"Tulip"* was pioneered in the Netherlands which grabbed the attention of large number of investors. The Netherlands population got excited about this tulip flower and began investing in it. In a short span of time, investing in this exotic flower became a fad which escalated its value tremendously. According to past studies, during the peak time, price of one bulb was higher than ten multiples of the annual pay of a worker. The bubble eventually burst when investors realized that they have devoted a large amount on a flower bulb and they began to sell them. As a result, the price plunged, leading to huge losses. Occurrences such as the tulip mania compels us to raise a simple query that 'are investors actually rational?' Since 1980s, a large number of researches have fostered some problems leading to over or under reaction of the investors, which has led to the rejection of the traditional EMH hypothesis. Behavioral finance is a new domain in the area of financial markets that has emerged in retort to hurdles faced by traditional paradigm. As per Sewell (2007), *"Behavioral finance is the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets."* Day to day investment related choices depend on amalgamation of various facets, such as, sentiments, logic, fondness, pattern and social interaction. The field of behavioral finance tries to elucidate why people make mistakes which further leads to market anomalies. Prior researches in this domain have examined the influence of behavioral anomalies particularly in the developed economies. However, the evidence from the Indian market is scant. This study is an effort to examine the existence of predominant biases in Indian stock market. These are herding, overconfidence bias, disposition effect, and the noise trading. The research is distinctive in the sense that it offers practical validation for the above-mentioned irrationalities at market level rather than generally analyzed conceptually at individual investor level.

2. Review of literature

The traditional finance theory has been challenged by researchers claiming that investors possess psychological and emotional anomalies and tend to act in an irrational manner. Behavioral finance is a recent finance domain that attempts to comprehend the role of emotions and cognitive mistakes in impacting investors' judgements. All the available relevant literature is cited here factor-wise to develop further the hypotheses examined under this study.

A. Herding

One of the most evident features of human being which is visible in social affairs is imitation which leads to herding. In other words, people learn basics in their lives by imitating others. Primarily, it is logical and wise to imitate others when people are short of sufficient time, energy and resources to take a decision. Individual investors display herd behavior as they are more willing to follow the decisions of popular analysts, large group, or noise traders. One of the reasons could be that a human being is a social animal and tend to seek acceptance from a group instead of being alone in a crowd. A large amount of research has investigated the presence of herding behavior in developed as well as emerging economies. The results are contradictory from country to country. Chiang & Zheng (2010) studied herding behavior in 18 countries worldwide for the time-period 1988-2009. Their research validated that crowding behavior exists in developed economies except for the United States. Khan et al. (2011) focused on herd behavior in European nations comprised of France, the UK, Germany, and Italy. It was concluded that the UK market shows less herding behavior than other countries. Also, during the market stress, herding can be seen more evidently than in other periods. Lindhe (2012) investigated the presence of herding in four Nordic states: Denmark, Finland, Norway, and Sweden and exhibited no market-wide herding behavior in Demark, Norway, and Sweden. However, significant evidence of herding was found in Finland. Chiang et al. (2013) tested herding behavior among investors for ten Pacific-Basin markets and established its presence. Kanojia et al. (2020) analyzed the market-wide herding in the Indian stock market and found no impact of herding on the stock returns in the Indian stock market during the normal market conditions. Prosad et al. (2012) demonstrated that herding behavior exists only in the period of stress. Lakshman et al. (2013) validated the herding bias's presence, specifically among the mutual fund investor. On the contrary, Jose et al. (2018) obtained no evidence of crowding in the Indian stock market as a whole. Dhall & Singh (2020) examined the herding behavior in the Indian stock market and established the non-existence of herding behavior at the industry level. However, the study validated herding behaviour during the covid-19 period.

B. Overconfidence Bias

According to Tapia & Yermo, 2007, "Overconfidence is the tendency for people to overestimate their knowledge, abilities and the precision of their information, for that reason investment decisions become based on conjecture rather than fundamental value". Prior surveys in this domain have enlightened the influence of the overconfidence on rational decision-making. They argue that the investors who overrate their investment trading skills are likely to engage more in trading due to high observed market returns (Daniel et al., 1998). Gervais & Odean (2001) revealed that overconfident investors trade more and increase their volatility, which in turn negatively influence their trading results and they suffer losses. Chuang & Lee (2006) have established a positive and significant link between current trading volume and lagged market returns that is in accordance with overconfidence bias. Statman et al. (2006) conducted study on USA stock market to investigate the presence of overconfidence bias and validated a positive association between market volume and past market returns, thereby, indicating the presence of overconfidence. Furthermore, Odean (1999) comprehended that investors become overconfident and engage in excess trading and suffer losses as they do not gain much to cover their transaction costs. Similarly, Barber & Odean (2000) found that excessive trading realized less returns. Zaiane (2013) examined the overconfidence bias in the Tunisian and Chinese markets and in both the markets, they demonstrated overconfidence bias. Tariq & Ulla (2013) investigated overconfidence bias in Pakistan stock exchange and found that lagged returns have positive impact on current turnover, which implies that Pakistani investors are overconfident. Prosad et al., (2013) exhibit overconfidence bias in Indian equity market.

C. Disposition effect

Shefrin & Statman (1985) introduced the disposition effect theory as a predominant bias in the domain of Behavioral finance. It states that investors are prone to sell the winning shares (whose price has increased) and tend to keep loss-making assets (whose price has dropped) as they are unwilling to realize losses but are more willing to realize gains prematurely. This occurs due to the belief that when investors sell a losing stock, the loss gets registered and is expected to give pain to the investors. To avoid such pain, investors prefer not to sell the losing stocks. Shefrin & Statman (1985) empirically proved that investors sell the winning stock and hold on to the loss-making asset. However, past studies have commented that during year-end, people are more eager to dispose of their loss-making investments, majorly due to tax motivation. Odean (1999) investigated the trading activity of household investors from the time period of 1987 to 1993. The study revealed that investors have a greater propensity to sell stocks that has risen in their value in comparison to the one whose value has decreased. Shumway & Wu (2006) find evidence of disposition effect by conducting a study on 13,460 Chinese investors. Moreover, many empirical studies (Bailey et al., 2011; Frazzini, 2006; Grinblatt & Keloharju, 2001; Weber & Camerer, 1998; Barberis & Xiong, 2009) have proved this bias. The literature reveals that this bias can have a detrimental effect on investing performance as the investors are not aware of when to quit and when to continue.

D. Noise trading

Noise trading refers to the concept wherein investors trade based on 'noise' in the market rather than information. Such traders ignore the fundamental knowledge and trade on the basis of gossip or rumor in the market. According to De Long et al. (1990), the presence of noise traders in stock markets creates a risk in the stock prices and causes prices to diverge significantly from their fundamental values even if all other investors are rational. Prior studies have determined the presence of noise trading in the stock markets by analyzing the causality between prices and trading volume. Noise traders momentarily manipulate the security price in the short run or take their investment decisions based on historical price changes. Therefore, a positively significant causality between trading volume and security prices is in accordance with the premise that price changes are the consequence of noise traders' actions. Shrestha (2017) observed unidirectional Granger causality from stock prices to trading volume in Nepalese stock market along with Heimstra & Jones (1994) in DJIA index, Jain & Joh (1988) in S&P 500 stocks, Chen et al. (2001) in nine developed stock markets, and Mahajan & Singh (2009) in Indian stock market, that is indicative of noise trading in the respective markets. Studies like Ghazali et al. (2011) and Al-Samman & Al-Jafari (2015) observed unidirectional Granger causality from trading volume to stock returns but not vice versa in the case of the DAX 30 index and Muscat securities market, respectively. On the contrary, Gunduz & Hatemi (2005) found no causality in the Chez Republic stock market and bidirectional relationship in the case of countries like Poland and Hungary. Also, Abdullahi et al. (2014) failed to show the presence of noise trading in West Texas Intermediates and Brent crude oil futures.

3.Research objectives

The study focuses on achieving the following specific objectives:

A. To determine the existence of herding in Indian stock market in the following situations:
   - Market as a whole,
   - Bullish and bearish phases of the stock market, and
   - Extreme market conditions.
B. To determine the existence of overconfidence bias and disposition effect in the Indian stock market in the following situations:
   - Market as a whole, and

- o on individual securities.

C. To determine the existence of noise trading in Indian stock market.

4. Hypotheses

In order to achieve the above objectives, the following hypotheses have been developed:

Hypothesis H_a1: *Herding bias has a significant impact on the Indian stock market*

Hypothesis H_a2: *Overconfidence bias has a significant impact on the Indian stock market*

Hypothesis H_a3: *Disposition effect has a significant impact on the Indian stock market*

Hypothesis H_a4: *Noise trading has a significant impact on the Indian stock market*

5. Data collection

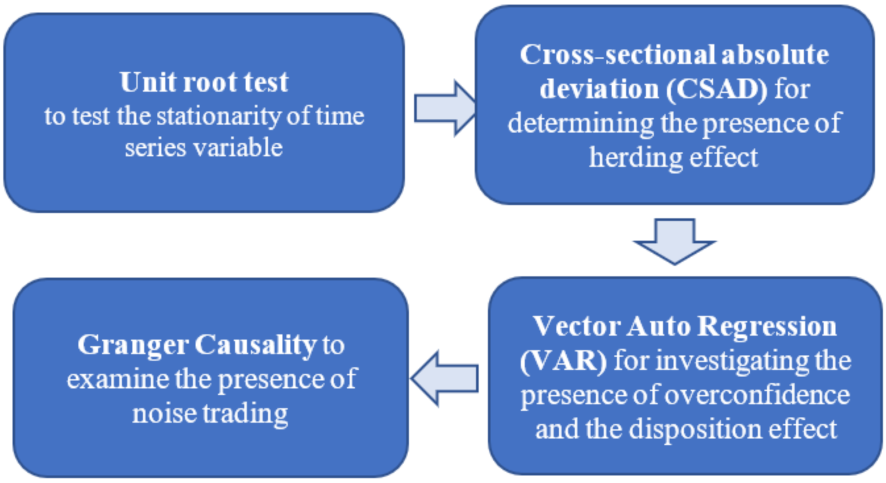
The paper has employed secondary data to validate the existence of behavioral factors or biases in Indian stock market. The data comprises of various market indicators (daily basis) of Nifty 50 stocks from January 1, 2000 to December 31, 2020, such as:

- Prices (closing, opening, high, low) of the index and individual stocks
- Transaction volume of the index and individual stocks.

The data has been obtained from the official NSE website.

6. Research methodology

The existence of the above-mentioned biases in stock market have been analyzed with the help of methodology as specified in the prior studies. Some of these techniques are specific to the particular biases. These techniques are shown in Figure 1.



Source: Author's contribution

Figure 1: Statistical Techniques used for Data Analysis

In line with pioneering studies, cross-sectional absolute deviation (CSAD) has been employed to investigate the presence of market-wide herding during normal market conditions and extreme market conditions in Indian stock market. Chang et al. (2000) proposed that individual stock return deviation would reduce when herd behavior follows. The author suggested that this relationship should be negative and non-linear in presence of herding (Chang et al., 2000). The nonlinear relationship is represented by following equation:

$$CSAD_t = \alpha + \beta_1|R_{mt}| + \beta_2 R^2_{mt} + e_t \quad \text{Eq. 1}$$

$$CSADt = \frac{1}{N}\sum_{s=1}^{n}|Rst - Rmt| \quad \text{Eq. 2}$$

where R_{st} represents stock return and R_{mt} is the market return. Here, the presence of a negative and significant β_2 represents herding.

Since the study has been carried out for an extensive time duration to capture the impact of behavioral biases in Indian stock market, it has been divided into four phases: - pre-crisis (2000-2007), during crisis (2008-2009), after crisis (2010-2019), and during covid crisis (Jan 2020-Dec 2020). This study has tried to investigate the presence of herding in different market conditions i.e., bull market, bear market, extreme up market, and extreme down market.

A. Testing herding on the overall market as a whole

In line with the methodology suggested by Chang et al., (2000), a non-linear (quadratic) regression model is run to determine the effect of market return on CSAD.

B. Testing herding in bullish and bearish market

Taking into consideration that the stock movements may be distorted during bull and bear phase of markets, the generalized relationship can be divided into following;

$$CSAD_t^{UP} = \alpha + \beta 1^{UP}|R_{mt}^{UP}| + \beta 2^{UP}(R^2_{mt}{}^{UP}) + \varepsilon_t \qquad R_{mt} > 0 \quad \text{Eq. 3}$$

$$CSAD_t^{DOWN} = \alpha + \beta 1^{DOWN}|R_{mt}^{DOWN}| + \beta 2^{DOWN}(R^2_{mt}{}^{DOWN}) + \varepsilon_t \qquad R_{mt} < 0 \quad \text{Eq. 4}$$

According to this method, statistically significant negative value of $\beta 2^{UP}$ and $\beta 2^{DOWN}$ captures herding.

C. Testing herding in Extreme up market and extreme down market

To test herding in the extreme market phases, regression model as suggested by "CCK (2000) model" run separately for extreme up (bullish) and extreme down (bearish) market using the daily data across all the two criteria 95% and 99%. The equations are:

$$CSAD_t^{UP} = \alpha + \beta 1^{UP}|R_{mt}^{UP}|\,|{*}D_t^{UP} + \beta 2^{UP}(R^2_{mt}{}^{UP}) {*}D_t^{UP} + \varepsilon_t \qquad R_{mt} > 0 \quad \text{Eq. 5}$$

$$CSAD_t^{DOWN} = \alpha + \beta 1^{DOWN}|R_{mt}^{DOWN}| {*}D_t^{DOWN} + \beta 2^{DOWN}(R^2_{mt}{}^{DOWN}) {*}D_t^{DOWN} + \varepsilon_t \quad R_{mt} < 0 \quad \text{Eq. 6}$$

In this case also, negative and significant $\beta 2^{UP}$ and $\beta 2^{DOWN}$ captures herding behavior.

Vector Auto Regression (VAR) is a type of time-series forecasting and is used to examine the existence of market anomalies, such as, overconfidence and the disposition effect. In this model, the overconfidence bias will be analyzed by running VAR model on market-wide trading volume and market returns. Also, disposition effect will be analyzed with the help of VAR on security-wide transaction volume and security returns, as proposed by Statman et al. (2006).

A. Market-wide VAR to determine overconfidence bias

In line with Statman et al., (2006) we have used a VAR model in order to analyze the association between daily market returns and transaction volume.

Here the endogenous variables are market transaction volume and daily market return, and the exogenous variable is the daily index volatility. The exogenous variable volatility has been included in this research to control for alternative explanations for trading activity.

$$Volume_t = \alpha + \sum_{J=1}^{k} \beta_i\, Volume_{t-j} + \sum_{J=1}^{k} \gamma_i\, MRT_{t-j} + \sum_{J=1}^{l} \nu_i\, Volatility_{t-j} + \varepsilon_\tau \qquad \text{Eq. 7}$$

$$MRT_t = \alpha' + \sum_{J=1}^{k} \beta'\, Volume_{t-j} + \sum_{J=1}^{k} \gamma'_j\, MRT_{t-j} + \sum_{J=1}^{l} \nu_i\, Volatility_{t-j} + \varepsilon_{2\tau} \qquad \text{Eq. 8}$$

Where:

$Volume_t$= daily transaction volume;

MRTt = daily stock returns;

Volatility = daily volatility of index computed by taking difference of using daily high and low prices.

Here, k is the number of lags for endogenous variables and l is number of lags for exogenous variable, decided on the basis of Akaike Information Criteria.

Here the positive value of γj captures the presence of overconfidence bias.

B. Security-wide VAR to determine disposition effect and overconfidence

The existing literature suggests that the transaction volume of individual stocks is positively related to past returns of that particular stock which captures the disposition effect, and past return of the overall market that captures the overconfidence.

$$Volume_t = \alpha + \sum_{J=1}^{k} \beta_i\, Volume_{t-j} + \sum_{J=1}^{k} \gamma_i\, SRT_{t-j} + + \sum_{J=1}^{k} \lambda_i\, MRT_{t-j} + \varepsilon_{1\tau} \qquad \text{Eq. 9}$$

k k k

$$SRT_t = \alpha' + \sum_{J=1}^{k} \beta' \, Volumet\text{-}j + \sum_{J=1}^{k} \gamma'_j \, SRT_{t-j} + + \sum_{J=1}^{k} \lambda'_j \, MRT_{t-j} + \varepsilon_{2\tau} \qquad \text{Eq. 10}$$

$$MRT_t = \alpha'' + \sum_{J=1} \beta'' \, Volumet\text{-}j + \sum_{J=1} \gamma''_j \, SRT_{t-j} + + \sum_{J=1} \lambda''_j \, MRT_{t-j} + \varepsilon_{3\tau} \qquad \text{Eq. 11}$$

Where:

$Volume_t$= daily transaction volume;

$MRTt$ = daily market returns;

SRT_t = daily stock returns;

and k = number of lag and has been decided based on Akaike Information Criteria.

According to the literature, the statistically significant positive value of γj indicates the existence of the disposition effect and positive value of λj indicates overconfidence.

Lastly, the **Granger causality test** the test has been used to examine the presence of noise trading in the stock exchange by determining the contemporaneous relation between market return and market transaction volume. Here, the null hypothesis (Ho) is that X-series do not explain the variation in Y, i.e., X(t) doesn't Granger-cause Y(t). If the p-value is less than 0.05, we do not accept the null hypothesis. In other words, X is Granger reason of variable Y.

7. Analysis and Discussion

The results for investigating the presence of herding, over-confidence, disposition effect, and noise trading in the Indian stock market have been presented and analyzed in following section:

A. Herding

The regression model results for determining the existence of herding on the aggregate market for the whole time period (2000-2020) and different phases of the market, i.e., pre-crisis (2000-2007), during the crisis (2008-2009), post-crisis (2010-2019), and during covid crisis (Jan 2020- Dec 2020), have been shown in table 1. Panel 1 of table 1 demonstrates the result for aggregate market as a whole. The results indicate the nonexistence of herd formation over the entire time period in the Indian stock market as the value of b2-coefficient [b2=0.102] is positive and significant. These results are in accordance with prior studies (Kanojia et al., 2020; Prosad et al., 2012; Jose et al., 2018, Ganesh et al., 2016), showing no sign of herding in the Indian stock market during a long period of time. Also, validating that the Indian investors does not mimic crowd behavior. Further, the coefficient value b2 is positive and significant (0.061, 0.076, and 0.148) in the different periods, i.e., before the crisis (2000-2007), during the crisis (2008-2009), and after the crisis (2010-2019), indicating the absence of herding behavior in all the time phases. The nonexistence of herding in the Indian stock market might be due to large institutional investors' impact as it is perceived that they have access to better information sources, more competent traders, and hence, are less likely to imitate. Moreover, due to extremely low participation of individual investment in Indian stock market, impact of herding is not evident. However, the results indicate the presence of herding behavior during the covid crisis period (Jan-Dec 2020) as the value of b2-coefficient [b2=-0.010] is negative and significant in the Indian stock market. Indian retail investors are scattered and have very little participation in the entire volume of trade. During different time periods spanning from 2000 to 2019, there have been many ups and downs in the stock market, but covid crisis period (March 2020-Dec 2020), was unprecedented, hence, longest ever retail participation exhibit herding during 2020. These results follow previous studies such as, Prosad et al. (2012) and Dhall & Singh (2020) validating the existence of herding behavior during crisis or stress time in the Indian stock market.

Panel B and C of Table 1 reveals the bull and bear market results, which suggest the nonexistence of herding in the bullish phase of the Indian stock market (as $b2^{BL}$-coefficient is positive and significant). Further, it may be deduced that there is no indication of herding in the bearish phase of the market for the overall time period (2000-2020), before crisis, during crisis, and after crisis period (positive and significant $b2^{BR}$). The excessively positive and significant b2 coefficient validates dispersion of stock returns from overall market returns, indicating the absence of a crowding mentality. On the contrary, the results indicate the presence of herding behavior during the covid crisis period as the value of b2-coefficient [b2=-0.006] is negative and significant. This indicates that mutual imitation is more evident in crisis situation as investors depend more on masses information instead of their own in times of heightened uncertainty. Moreover, due to panic and fear of loss during crisis, individuals sell their securities by imitating or following others particularly when the market is in its bearish phase.

In the literature, it was suggested that investors follow the group consensus to seek conviction and conformity in the extreme market stress phase. They do not follow their own judgment or belief to avoid the fretfulness of making erroneous decisions during market stress uncertainty and thereby leading to herding. This study intends to capture the existence of herding in the extreme up and extreme down market. Panel D -G show results of regression results for extreme market conditions. Here, 5% and 1% criteria have been used as cut-off points to decide extreme up and down-market conditions. Panel D shows that the value of coefficient b2 is negative and significant for the whole period (2000-2020) [b2=-0.025] and after the crisis period (2010-

2019) [b2=-0.003], thereby, affirming the presence of crowding behavior in Indian stock market in an extremely down market. Panel E shows a negative and significant value of b2 [b2=-0.048] during the crisis period (2008-09) in the extreme upmarket, indicating the presence of more severe herding behavior during the crisis period in the Indian stock market. Similarly, panel F shows a significantly negative value of b2 for the whole period [b2=-0.101] and before the crisis period [b2=-0.028] validates the presence of herd mentality in the extremely down market. Also, panel G shows a significantly negative value of b2 for the after the crisis period [b2=-0.140] affirming the presence of crowding.

Table 1: Regression outcome for CSAD and market return for overall market level and different time phases

Panel	Variable	Whole Period (2000-2020)	Before crisis (2000-2007)	During crisis (2008-09)	After the crisis (2010-2019)	Covid crisis (Jan-Dec 2020)
A. Aggregate Makret	α	1.476*	1.484*	2.089*	1.396*	1.118*
	b1	0.218*	0.358*	0.236*	-0.048*	0.374*
	b2	0.102*	0.061*	0.076*	0.148*	**-0.010****
B. Bull Market	α	1.436*	1.570*	2.006*	1.363*	1.116*
	b1	0.186*	0.024*	0.315*	-0.032	0.375*
	b2	0.167*	0.222*	0.097*	0.179*	0.003
C. Bear Market	α	1.471*	1.536*	2.178*	1.334	1.158*
	b1	0.378*	0.399*	0.111*	0.242	0.298*
	b2	0.007*	0.004*	0.082*	0.012	**-0.006***
D. Extreme down market (5%)	α	0.985*	1.422*	2.73*	1.337*	3.563**
	b1	0.666*	0.439**	-0.233**	0.256*	-0.385
	b2	**-0.025***	0.001*	0.129**	**-0.003***	0.034
E. Extreme upmarket (5%)	α	0.481	1.684*	0.191**	-0.135	1.096*
	b1	0.754*	-0.083*	1.458	0.851*	1.463**
	b2	0.109*	0.239*	**-0.048****	0.103*	-0.101
F. Extreme down market (1%)	α	-1.139*	0.54*	4.93	1.998	NA
	b1	1.533**	0.781**	-1.217	-0.008	NA
	b2	**-0.101****	**-0.028***	0.237	0.019	NA
G. Extreme upmarket (1%)	α	-1.765*	-0.108*	-0.809	-8.094*	NA
	b1	1.609*	0.778*	1.707	4.031*	NA
	b2	0.042*	0.144*	-0.06	**-0.14***	NA

NA-Data not sufficient

**Significant at 1%   **Significant at 5%*

Source: Research Output

Thus, herding is exhibited during extreme market conditions and might be caused by the irrational exuberance of individual investors who can easily be manipulated or influenced by media or blinded by greediness. Indian investors develop fear of missing out (FOMO) or lagging behind when their friends, colleagues, and relatives seems like making money, which drives them to follow the crowd. Also, Indian investors exhibit herding during crisis period, especially when market crisis is the most talked information covered in news, internet, by experts, non-experts, entertainment magazines, tea-time conversations, etc. During such phase, anchoring bias, representativeness bias, loss aversion bias, mental accounting bias, all indicate towards one action which is taken by majority of retail investors, thereby leading to herding. On the basis of above findings, we may reject null hypothesis (H_o1), which states that herding bias does not exist in the Indian stock market. The findings of this research are consistent with preceding studies, such as Lao & Singh (2011), Prosad et al. (2012), etc.

B. Overconfidence bias- Result for market-wide VAR

As the preceding section provides empirical evidences for herding captured in Indian stock markets, this section details the evidences for overconfidence bias. In line with Statman et al. (2006) and Prosad et al. (2013), overconfidence bias has been analyzed by running the VAR model on market-wide trading volume and market returns. This study has tried to investigate the presence of overconfidence bias for the overall time period of 21 years and separately for pre-crisis (2000-2007), during crisis (2008-2009), after crisis (2010-2019), and during covid crisis (Jan 2020-Dec 2020) periods.

For choosing the optimal lag length, prior literature offers various alternatives such as Akaike information criterion (AIC), Hannah-Quinn (HQ), Schwarz information criteria (SIC), and final prediction error (FPE). There is no hard and fast rule with respect to selecting the best criterion for determining the optimal lag length. In line with prior studies (Phan et al., 2020 and Zia et al., 2017), an optimal lag selection has been based on Akaike (AIC), as shown in table 2. "Akaike information criteria are most popular in identifying the lag of endogenous variables." (Zia et al., 2017).

Table 2: Optimal lag selection

Whole Period (2000-2020)				**Before crisis (2000-2007)**				**During crisis (2008-09)**				**After the crisis (2010-2019)**				**Covid crisis (Jan-Dec 2020)**			
AIC(n)	HQ(n)	SC(n)	FPE(n)	AIC(n)	HQ(n)	SC(n)	FPE(n)	AIC(n)	HQ(n)	SC(n)	FPE(n)	AIC(n)	HQ(n)	SC(n)	FPE(n)	AIC(n)	HQ(n)	SC(n)	FPE(n)
10	10	8	10	10	10	5	10	6	6	5	10	10	9	8	10	10	6	1	10

Source: Research Output

After determining the optimal lag length, we estimated VAR to analyze the association between daily market returns and transaction volume. Table 3 provide the results of equation VAR. For each variable, we have reported the coefficient value, t statistic and p-value. Consistent with our supposition from the overconfidence hypothesis, the results reveal that many of the lagged MRT coefficients (market return) in the volume regression are positive and statistically significant (refer table 3). To be specific, the daily trading volume of the Nifty 50 index is positively and significantly related to the first, second, and sixth lag of market return. This result validates the existence of overconfidence bias in the Indian stock market for the whole time period (2000-2020). On the basis of above findings, we may reject second null hypothesis (H_o2), which states that overconfidence bias does not exist in the Indian stock market. The findings of this research are consistent with prior studies of overconfidence such as, Prosad et al. (2013) and Kanojia et al. (2020). The findings also support studies like Statman et al. (2006), Chuang & Lee (2006), Zaiane (2015), though the results depict scenario from USA and China. Further, table 3 shows the results to determine the overconfidence bias in the different periods, i.e., before the crisis, during the crisis, after the crisis, and during covid crisis. The overconfidence hypothesis is verified for the first lag (MRT_{-1}) (as the coefficient value (γ_p) is positive and significant at a 5% level) for before crisis and during crisis period. However, none of the coefficients on lagged MRT (market return) in the volume regression is positive and statistically significant for after crisis and during covid crisis periods. In other words, our findings do not validate the existence of overconfidence bias in the Indian stock market after 2008-09 crisis. It might be due to the fact that after crisis, institutional investors have started using long-term holding as a strategic option against short term trading. Investors have started following Warren Buffett's 'buy and hold' strategy which implies that investments should be made in businesses that will endure to offer a competitive advantage decade down the line. He mentioned in his letter to shareholders, "if you aren't willing to own a stock for ten years, don't even think about owning it for ten minutes" (Buffett & Clark, 2008). Individual investors also participate indirectly in the stock market through pension funds, mutual funds, and ulip plans which require blocking of funds for a longer period of time. Though the overall participation in stock market has increased after crisis along with the increasing market return, still its impact is not much reflected on transaction volume as investors focus has shifted to investments with long-term horizons instead of short-term trading. Moreover, Indian investors have recently opened 14.2 million new demat accounts in financial year 2021, an all time high in its history (Livemint, April 2021). This is an increase of approximately three times the new accounts opened in the previous financial year. This indicates a significant increase in retail investors participation in overall stock market, however, its impact on transaction volume will be visible in future only when they will start transacting more. Subsequent to that we will be able to validate the existence of overconfidence bias in the Indian stock market in post crisis period.

Table 3: Market VAR estimation (Indian stock market)

Whole Period (2000-2020)

	Estimate	t value	P value
const	9.04766	1.97909	4.95e-06 ***
MRT.l1	**1.16577**	**1.965**	**0.04945 ***
MRT.l2	**1.04013**	**1.066**	**0.04724***
MRT.l3	0.54070	0.889	0.37418
MRT.l4	0.04020	0.066	0.94739
MRT.l5	0.45397	0.746	0.45591
MRT.l6	**1.07066**	**1.762**	**0.04805***
MRT.l7	-0.43096	-0.710	0.47780
MRT.l8	-0.93509	-1.547	0.12191
MRT.l9	0.58405	0.971	0.33153
MRT.l10	0.28717	0.488	0.62558
volatility.l1	315.54348	3.563	0.00037 ***
volatility.l2	-150.51064	-1.63	0.10297
volatility.l3	56.36476	0.608	0.54306
volatility.l4	-174.91964	-1.884	0.05964 .
volatility.l5	-190.57907	-2.046	0.04078 *
volatility.l6	-99.65564	-1.070	0.28451
volatility.l7	-183.89493	-1.983	0.04739 *
volatility.l8	-49.11122	-0.531	0.59537
volatility.l9	262.95597	2.860	0.00425 **
volatility.l10	-45.89929	-0.529	0.59690
VOLUME.l1	0.41144	29.247	< 2e-16 ***
VOLUME.l2	0.08435	5.556	2.89e-08 ***
VOLUME.l3	0.13045	8.572	< 2e-16 ***
VOLUME.l4	0.06114	4.008	6.22e-05 ***
VOLUME.l5	0.07690	5.037	4.89e-07 ***
VOLUME.l6	0.03042	1.992	0.04643 *
VOLUME.l7	0.10520	6.885	6.48e-12 ***
VOLUME.l8	0.02882	1.889	0.05890 .
VOLUME.l9	0.02918	1.919	0.05500 .
VOLUME.l10	0.01869	1.329	0.18385

Before crisis (2000-2007)

	Estimate	t value	P value
const	5.43490	4.477	8.01e-06 ***
MRT.l1	**0.87322**	**3.133**	**0.001754 ****
MRT.l2	0.32700	1.128	0.259629
MRT.l3	0.34826	1.196	0.231834
MRT.l4	0.13751	0.471	0.637412
MRT.l5	-0.04051	-0.139	0.889798
MRT.l6	-0.28338	-0.971	0.331646
MRT.l7	-0.18833	-0.648	0.517163
MRT.l8	-0.08381	-0.290	0.771832
MRT.l9	0.01120	0.039	0.968900
MRT.l10	-0.04497	-0.166	0.868442
volatility.l1	162.06734	3.824	0.000135 ***
volatility.l2	-54.45727	-1.227	0.219957
volatility.l3	-40.68144	-0.908	0.363767
volatility.l4	18.38827	0.411	0.680785
volatility.l5	-169.95863	-3.787	0.000157 ***
volatility.l6	-10.59234	-0.235	0.814154
volatility.l7	-5.10589	-0.114	0.909283
volatility.l8	6.43738	0.143	0.886039
volatility.l9	16.16478	0.364	0.715752
volatility.l10	-15.04078	-0.370	0.711678
VOLUME.l1	0.46802	19.957	< 2e-16 ***
VOLUME.l2	0.02951	1.145	0.252166
VOLUME.l3	0.15982	6.177	7.92e-10 ***
VOLUME.l4	0.02721	1.040	0.298341
VOLUME.l5	0.21284	8.141	6.88e-16 ***
VOLUME.l6	-0.03605	-1.378	0.168284
VOLUME.l7	-0.01340	-0.512	0.608851
VOLUME.l8	0.02446	0.943	0.345557
VOLUME.l9	-0.00308	-0.119	0.905284
VOLUME.l10	0.08418	3.608	0.000316 ***

During crisis (2008-09)

	Estimate	t value	P value
const	17.55208	2.167	0.030726 *
MRT.l1	**3.46829**	**3.499**	**0.000512 *****
MRT.l2	1.73885	1.700	0.089807 .
MRT.l3	0.61767	0.599	0.549495
MRT.l4	0.92212	0.902	0.367702
MRT.l5	0.69327	0.677	0.498718
MRT.l6	0.82084	0.819	0.412979
volatility.l1	1227.98499	8.144	3.57e-15 ***
volatility.l2	-349.95755	-2.075	0.038563 *
volatility.l3	-259.16389	-1.545	0.123079
volatility.l4	-343.93476	-2.061	0.039885 *
volatility.l5	-229.59180	-1.359	0.174703
volatility.l6	145.59225	0.915	0.360697
VOLUME.l1	0.45510	9.759	< 2e-16 ***
VOLUME.l2	0.16450	3.234	0.001308 **
VOLUME.l3	0.04181	0.817	0.414141
VOLUME.l4	0.06781	1.317	0.188454
VOLUME.l5	0.07050	1.377	0.169149
VOLUME.l6	0.09587	2.208	0.027715 *

After the crisis (2010-2019)

	Estimate	t value	P value
const	17.71716	3.563	0.000373 ***
MRT.l1	0.97264	0.712	0.476392
MRT.l2	-1.31224	-0.953	0.340500
MRT.l3	-0.86592	-0.626	0.531625
MRT.l4	1.41274	1.016	0.309539
MRT.l5	-0.57191	-0.411	0.680757
MRT.l6	-0.01964	-0.014	0.988717
MRT.l7	1.49935	0.531	0.344204
MRT.l8	-1.51408	-1.095	0.273549
MRT.l9	0.86854	0.630	0.528874
MRT.l10	1.32311	0.963	0.335846
volatility.l1	248.14453	1.213	0.225170
volatility.l2	255.35336	1.253	0.210397
volatility.l3	223.62344	1.095	0.273513
volatility.l4	272.26581	1.335	0.182124
volatility.l5	-436.43030	-2.128	0.033429 *
volatility.l6	-257.81838	-1.257	0.208768
volatility.l7	-881.70396	-4.324	1.59e-05 ***
volatility.l8	-584.64472	-2.863	0.004238 **
volatility.l9	449.69993	2.211	0.027148 *
volatility.l10	-45.34606	-0.223	0.823411
VOLUME.l1	0.28247	13.691	< 2e-16 ***
VOLUME.l2	0.08617	4.026	5.85e-05 ***
VOLUME.l3	0.11333	5.329	1.08e-07 ***
VOLUME.l4	0.03000	1.413	0.157804
VOLUME.l5	0.10046	4.727	2.40e-06 ***
VOLUME.l6	0.00559	0.263	0.792542
VOLUME.l7	0.11541	5.410	6.93e-08 ***
VOLUME.l8	0.14513	6.807	1.25e-11 ***
VOLUME.l9	0.02653	1.237	0.216377
VOLUME.l10	0.05667	2.739	0.006205 **

Covid crisis (Jan – Dec 2020)

	Estimate Std. Error	t value	Pr(>|t|)
const	1.590e+02	2.379	0.01826 *
MRT.l1	-1.781e+00	-0.295	0.76792
MRT.l2	-5.151e+00	-0.803	0.42308
MRT.l3	3.400e+00	0.545	0.58642
MRT.l4	-1.073e+01	-1.686	0.09324 .
MRT.l5	1.611e+00	0.253	0.80041
MRT.l6	-1.033e+01	-1.759	0.08000 .
MRT.l7	1.197e+00	0.207	0.83585
MRT.l8	-1.017e+01	-1.761	0.07973 .
MRT.l9	-4.504e-01	-0.079	0.93744
MRT.l10	-5.457e+00	-0.965	0.33558
volatility.l1	-2.005e+03	-2.099	0.03701 *
volatility.l2	-7.367e+02	-0.762	0.44698
volatility.l3	1.793e+03	1.914	0.05695 .
volatility.l4	-1.087e+03	-1.135	0.25765
volatility.l5	1.207e+03	1.296	0.19636
volatility.l6	-1.649e+03	-1.757	0.08037 .
volatility.l7	-4.032e+02	-0.418	0.67646
volatility.l8	4.992e+02	0.523	0.60171
volatility.l9	1.293e+03	1.306	0.19298
volatility.l10	4.127e+02	0.425	0.67123
VOLUME.l1	6.739e-01	9.592	< 2e-16 ***
VOLUME.l2	-9.893e-02	-1.194	0.23374
VOLUME.l3	1.358e-01	1.682	0.09401 .
VOLUME.l4	1.472e-01	1.824	0.06953 .
VOLUME.l5	-1.009e-01	-1.263	0.20799
VOLUME.l6	1.780e-01	2.235	0.02650 *
VOLUME.l7	8.592e-02	1.069	0.28649
VOLUME.l8	-2.130e-01	-2.646	0.00876 **
VOLUME.l9	1.624e-01	1.998	0.04695 *
VOLUME.l1	-1.863e-01	-2.531	0.01209 *

*Significant codes: '***' 0.001 '**' 0.01 '*'0.05* Volume= daily transaction volume of index; MRT = daily stock returns of N number of stocks, which has been calculated by difference of successive day's closing price divided by previous day closing price of the index, Volatility = daily volatility of index computed by taking the difference of using daily high and low prices

Source: Research Output

C. *Overconfidence bias and disposition effect- Result for security-wide VAR*

The existing literature suggests that individual stocks' transaction volume is positively related to past market return that captures the overconfidence bias. However, disposition effect occurs when individual stocks' transaction volume is positively related to its own past returns because investors enjoy realizing gain on individual securities. Therefore, investors are prone to sell the winning shares (whose price has increased) and tend to keep loss-making assets (whose price has dropped) as they are unwilling to realize losses but are more willing to realize gains prematurely, thereby leading to disposition effect (Statman et al., 2006; Prosad, 2013; Zaine, 2013). VAR model has been used to test the hypothesis H_O3, i.e., existence of disposition bias in the Indian stock market. Disposition effect has been analyzed by running the VAR model on security-wide transaction volume and security returns. The statistically significant positive value of γp (in equation 3) indicates the disposition effect's existence, and the positive value of λp indicates overconfidence. Our findings demonstrate that out of total 50 securities, the disposition effect and overconfidence bias has been identified in 9 and 14 companies respectively as shown in table 4. This demonstrates that overconfidence bias is predominant amongst the two. Out of these companies, 7 are common which have been affected by both biases. Table 4 infers that overconfidence bias and disposition effect are more visible in stocks having high PE ratio or have high market capitalization, such as, Bajaj Finserv Ltd., Eicher Motors Ltd., ICICI Bank Ltd., Kotak Mahindra Bank Ltd., Maruti Suzuki India Ltd., Reliance Industries Ltd. Tata Motors Ltd., and others. These are the stocks which investors keep on buying even at a premium price. Looking at the effect of investors' behavior on transaction volume instigate us to question the validity of conventional financial theories. High transaction volume might impact the stock prices in a biased manner that may not be validated by their price/earnings (P/E) ratio. This might lead to overvaluation or undervaluation of stocks. Thus, we may reject null hypothesis (H_o3), i.e., Disposition effect does not exist in the Indian stock market.

Table 4: List of Nifty 50 affected by Over-confidence Bias and Disposition Effect

Company Name	Overconfidence Bias	Disposition Effect
Adani Ports and SEZ Ltd.	Yes (Lag 1,2)	No
Asian Paints Ltd.	Yes (Lag 1,2,5)	No
Axis Bank Ltd.	Yes (lag 2, 5)	Inconclusive (Lag 2)
Bajaj Finserv Ltd.	Yes (Lag 2,3)	Yes (Lag 1,2)
Eicher Motors Ltd.	Yes (Lag 6)	Yes (Lag 1,2,3)

Grasim Industries Ltd.	Yes (Lag 1,2)	No
ICICI Bank Ltd.	Yes (Lag 1)	Inconclusive (Lag 1,4,5,7,9)
Kotak Mahindra Bank Ltd.	Yes (Lag 1,2,5)	Yes (Lag 1,2)
Maruti Suzuki India Ltd.	Yes (Lag 1)	Yes (Lag 1,2)
Oil & Natural Gas Corporation Ltd.	No	Yes (Lag 1)
Reliance Industries Ltd.	Yes (lag 1,5)	No
State Bank of India	Yes (Lag 1)	No
Tata Motors Ltd.	Yes (Lag 1,4)	Yes (Lag 1,4,7,8)
Tech Mahindra Ltd.	Yes (Lag 1,4)	Yes (Lag 1,2)
UPL Ltd.	No	Yes (Lag 1)
Zee Entertainment Enterprises Ltd.	Yes (Lag 1,2)	Yes (Lag 1,3,5)

Source: Research Output

D. Results for Granger Causality

According to De Long et al. (1990), the presence of noise traders in stock markets creates a risk in the stock prices and causes prices to diverge significantly from their fundamental values even if all other investors are rational. Table 5 documents the result for granger causality test which has been used to investigate the contemporaneous relation between market return and market transaction volume in the Indian stock market. On the basis of findings shown in table 5, it could be claimed that market return granger cause market transaction volume. However, the market volume is not found to granger cause or forecast market return as P-value > 0.05. Therefore, we can say that there is unidirectional causality from the market return to market transaction volume that proves noise trading in the Indian Stock market. Thus, we may reject the null hypothesis (H_o4). In other words, there exists a significant presence of noise trading in the Indian stock market. Our findings provide support to prior studies, such as Mahajan & Singh (2009) in Indian stock market, Heimstra & Jones (1994) in DJIA index, Jain & Joh (1988) in S&P 500 stocks, Chen et al. (2001) in nine developed stock markets, and Shrestha (2017) in Nepalese stock market.

Table 5: Granger Causality for Market Transaction Volume versus Market Return

Null Hypothesis	**F-statistic**	**p-value**
VOLUME does not Granger Cause RETURN	1.4233	0.2329
RETURN does not Granger Cause VOLUME	6.7851	0.009219**

Signif. code: '**' 0.01

8. Conclusion

This study has tried to determine the existence of the predominant behavioral anomalies; the herding bias, disposition effect, overconfidence bias, and noise trading in Indian stock market. The result of the research shows that Indian stock markets are efficient as we fail to validate the existence of herding for the overall market as well as during the pre-crisis period, crisis period and post- crisis period. The results are in accordance with prior studies like Lakshman et al. (2011); Prosad et al. (2012); Jose et al. (2018), showing no sign of herding in Indian stock market as a whole. Also, validating that the Indian investors are well apprised and rational in investment decisions, they don't mimic the behavior of crowd. It might be because of the influence of large institutional investors as it is perceived that they have access to better information sources, more competent traders, and hence, are less probable to imitate. However, the results indicate the presence of herding behavior during the covid crisis period for the overall market and bearish market. Moreover, herding is found to be evident in extreme market conditions (5% and 1%). It may be because investors pursue the market crowd due to the irrational exuberance of individual investors who can easily be manipulated or influenced by the media or blinded by greediness. Indian investors develop fear of missing out (FOMO) or lagging behind when their friends, colleagues, and relatives seems like making money, which drives them to follow the crowd. Also, Indian investors exhibit herding during crisis period, especially when market crisis is the most talked information covered in news, internet, by experts, non-experts, entertainment magazines, tea-time conversations, etc. During such phase, anchoring bias, representativeness bias, mental accounting bias, all indicate towards one action which is taken by majority of retail investors, thereby leading to herding. These results follow previous studies such as, Prosad et al. (2012) and Dhall & Singh (2020) validating the existence of herding behavior during crisis or stress time in the Indian stock market.

The results also validate the existence of anomalies such as overconfidence, disposition effect, and noise trading in Indian stock market. Findings of this research are consistent with prior studies, such as Statman et al. (2006), Chuang & Lee (2006), Zaiane (2013), Prosad et al. (2013), etc. in the manner that the transaction volume at overall market level escalates when people become overconfident whereas it rises at individual security level to demonstrate disposition effect. This study provides conclusive evidence for presence of the behavioral biases in the Indian stock market. These biases impact the performance of investors' individual portfolios, consequently impacting the overall wealth generated by them. Moreover, investors are more susceptible to behavioral anomalies during market crashes and react irrationally due to the fear and panic caused by the uncertainty. Indian stock markets have encountered many roller coaster rides in their history wherein acute crashes and sharp corrections have led to severe stock market crashes. Such turbulence in the markets has made it challenging for ordinary investors to behave rationally and to thrive and generate consistent returns through such an arduous phase. Thus, it is imperative to eliminate these biases to help investors survive market crashes. Although investors cannot circumvent all behavioural errors, but they can try to reduce their effects. The best way to avoid these biases requires a proper understanding of one's behavioural mistakes, resisting the propensity to engage in such behaviours, and formulating and implementing rational and objective investment strategies. Investors are also required to devote their resources for the longer horizon, assess their risk appetite, establish an apt asset allocation strategy, and rebalance their portfolios periodically. Always remember, the secret to float during turbulence is to remain unemotional and examine the scenario in a calm and logical manner. This will definitely lead to judicious investment decisions.As every study is constrained by time and resources, so do the present study is subject to few limitations. The study has included only selected Indian companies. Future research can be conducted on enlarged sample size to check the consistency of the results. Future research can focus on other countries as well to determine whether worldwide investors encounter same behavioural biases or are there any differences. Moreover, this study has taken into consideration only a few behavioral anomalies, while many other biases, such as, anchoring, loss aversion, representativeness, mental accounting, etc. have not been taken into consideration and these can be incorporated for further researches in future.

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