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Investors overconfidence behaviour at Bombay Stock Exchange

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Abstract

Purpose – The purpose of the paper is to empirically test the overconfidence hypothesis at Bombay Stock Exchange (BSE).

Design/methodology/approach – The study applies bivariate vector autoregression to perform the impulse-response analysis and EGARCH models to understand whether there is self-attribution bias and overconfidence behavior among the investors.

Findings – The study shows the empirical evidence in support of overconfidence hypothesis. The results show that the overconfident investors overreact to private information and underreact to the public information. Based on EGARCH specifications, it is observed that self-attribution bias, conditioned by right forecasts, increases investors' overconfidence and the trading volume. Finally, the analysis of the relation between return volatility and trading volume shows that the excessive trading of overconfident investors makes a contribution to the observed excessive volatility.

Research limitations/implications – The study focused on self-attribution and overconfidence biases using monthly data. Further studies can be encouraged to test the proposed hypotheses on daily data and also other behavioral biases.

Practical implications – Insights from the study suggest that the investors should perform a post-analysis of each investment so that they become aware of past behavioral mistakes and stop continuing the same. This might help investors to minimize the negative impact of self-attribution and overconfidence on their expected utility.

Originality/value – To the best of the authors' knowledge, this is the first study to examine the investors' overconfidence behavior at market-level data in BSE, India.

Keywords Overconfidence, Behavioural finance, Excessive volatility, Over/Underreaction, Self-Attribution bias

Paper type Research paper

1. Introduction

The conventional asset-pricing models rest on an important assumption that agents behave rationally. However, many empirical literatures consistently demonstrate that those models fail to explain the stylized facts observed in securities markets[1]. A growing number of researchers argue that one critical reason for the failure of the conventional asset-pricing model is primarily due to the inappropriateness of rationality assumption. By relaxing this seemingly unrealistic assumption, some models are developed basing on special trading strategies taken by irrational investors to explain the observed anomalies while others are derived based on investors' cognitive bias to solve the difficulties encountered by the traditional finance paradigm[2].

Recently, several behavioral finance models have been motivated by offering a unified explanation of short-run underreaction and long-run overreaction. For example, Daniel *et al.* (1998) argued that if investors are overconfident, they overweight their own private information at the expense of ignoring publicly available information. As a result of overconfidence, investors overreact to private information and underreact to public information. They showed that this asymmetric response of overconfident investors to

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private information and public information induce short-horizon momentum and long-horizon reversals in returns.

It has been argued that trading volume in speculative markets is too large to be justified on rational grounds. Trading motivated from hedging and liquidity purposes seems to explain only a small fraction of the observed trading activity and fails to support a substantial amount of trade in the real world. Overconfidence has been advanced as an explanation for the observed excessive trading volume. For example, Gervais and Odean (2001) developed a model predicting that investors mistakenly attribute market gains to their ability to pick up winner stocks, and the process of wealth accumulation makes them overconfident. Because of rising overconfidence investors trade more aggressively subsequent to the up state of the market. Similar argument that greater overconfidence leads to greater trading also is made by De Long *et al.*, Kyle and Wang, Benos (1998), Odean (1998), Wang (2001), Daniel *et al.* (2001) and Hirshleifer and Luo. De Bondt and Thaler (1995, p. 393) stated, "the key behavioral factor needed to understand the trading puzzle is overconfidence."

2. Literature review

Behavioral finance is one best approach to explain investor irrationality. Researchers attribute the behavioral biases of investors and stock market anomalies to psychological concepts such as overconfidence. Odean (1998) argued that investors are overconfident of their abilities, knowledge and future expectations. This makes them trade more excessively for a lower level of expected utility. The empirical evidence supports this argument (Odean, 1998, 1999; Benos, 1998; Barber and Odean, 2000, 2001; Grinblatt and Keloharju, 2009; Trinugroho and Sembel, 2011). Other studies find that overconfidence affects the trading volume in addition to trading frequency. Glaser and Weber and Statman *et al.* showed that high overconfidence investors have a propensity to trade in large volumes. Bloomsfield *et al.*, Biais *et al.*, Kirchler and Maciejovsky and Pompian argued that overconfident investors achieve lower returns than rational investors. However, overconfidence differs from one culture to another (Lee *et al.*, 1995; Whitcomb *et al.*, 1995; Yates *et al.*, 1997, 1998; Chuang and Lee, 2006).

Daniel *et al.* (1998) proposed a model where overconfidence causes overreaction to private information that investors have worked hard to generate and underreaction to more important public information, implying long-run reversals. Self-attribution bias causes overreactions to continue as later public information arrives, implying short-run momentum and long-run reversals. Odean (1998) made the effort to attempt to explain the observed excessive trading and volatility. Overconfident traders in his model believe their private information to be more precise than it is. He showed that both expected trading volume and volatility increase with the degree of investors' overconfidence. He argued that when there are many overconfident traders, markets tend to underreact to abstract, statistical and highly relevant information and overreact to salient but less relevant information. Daniel and Titman offered a simple model that explicitly distinguishes between tangible information and intangible information. They showed that stock prices overreact to intangible information rather than tangible information and concluded that their findings are consistent with the evidence in the psychology literature suggesting that individuals react differently to information that is difficult to interpret.

Statman *et al.* (2006) tested the market trading volume prediction of formal overconfidence models and found that turnover is positively related to lagged returns for months and perhaps years, even after controlling for turnover trend and contemporaneous volume-volatility relationships. The results are consistent with disposition effect trading in conjunction with the trading volume prediction of investor overconfidence. Moreover, both overconfidence and disposition effect trading are more pronounced in small-cap stocks and in earlier periods where individual investors hold a greater proportion of shares. They also tested the return autocorrelation predictions of formal overconfidence models and found some confirmatory results.

De *et al.* (2011) have studied the relative effects of disposition effect and investor overconfidence in the Indian context. The data include the entire universe of transactions and order records of all 755 stocks that traded on the NSE between January 1, 2005 and June 30, 2006. Using unified framework they have compared the effects of a particular behavioral bias, disposition effect or overconfidence, as the case may be, on performance across investor categories. Their findings, in general, suggest that economic effects of behavioral biases on trading performance are worse for individual investors than for the other investor categories. Moreover, overconfidence results in more wealth loss than disposition effect. In this respect, the findings are consistent with the accumulated evidence (Carhart, 1997; Odean, 1999; Barber and Odean, 2000, 2001).

Ashish Kumar Garg and Pankaj Varshney (2015) have examined the existence of a momentum effect in the Indian stock market using four sectors (auto, banking, pharma and IT sectors) of Indian economy covering the period from May 2000 to April 2013 using a sample comprising large cap stocks from CNX 500. Their analysis revealed the existence of momentum effect in the Indian stock market supporting the behavioral explanation given by the Daniel *et al.* (1998) and Hong and Stein (1999) that momentum profit is a result of initial underreaction of the traders followed by subsequent overreaction. The other reasons for momentum phenomenon are initial underreaction and eventual overreaction to firm-specific news (Chan *et al.*, 1996; Hong and Stein, 1999) and investors' overconfidence about their own abilities (Daniel *et al.*, 1998).

Pramod Kumar Naik and Puja Padhi (2015) studied the impact of information flow into the market on asymmetric volatility in four emerging markets economies (Brazil, Russia, India and China) for the period 2008–2013. It is found that the asymmetric effects in the equity return volatility are statistically significant for all the four countries over the study period. The findings signify that current market volatility in these countries is an asymmetric function of lagged volatility and negative shocks cause more volatility than positive shocks of the same magnitude indicating the existence of "leverage effect."

Jyoti Kumari and Jitendra Mahakud (2015) empirically studied the relationship between investor sentiment and stock returns volatility in Indian stock market. The results find persistence of volatility and volatility patterns of clustering, asymmetry and leverage effect which is associated with investors past psychological biases and herding nature.

Jaya M. Prosad *et al.* (2017) investigated the presence of the disposition effect and overconfidence in the Indian equity market during the period April 1, 2006 to 31 March, 2013 and provided some robust empirical evidence. The sample consists of daily total returns and transaction volume for each constituent stock and total returns of NSE Nifty 50 Index. The study arrives at three key findings. First, the presence of the biases, overconfidence and the disposition effect is detected in Indian equity market. Second, the impact of these two biases can be distinctly segregated for 20 companies among the companies in the index. Third, the overconfidence bias is found to be predominant of the two biases.

3. Data and descriptive statistics

All the stocks at Bombay Stock Exchange (BSE) which have information on monthly adjusted closing prices, shares traded, shares outstanding and market capitalization are considered for the study. Based on these criteria, the sample consisting of 1,290 stocks traded on BSE during April 2004 to March 2012 is considered for the study.

The data are split into two parts—first, April 2004 to September 2008 which includes economic growth period of 2004–2005 to 2007–2008. Second, October 2008 to March 2012 in order to understand the post-crisis scenario. The rationale of selecting the first period from April 2004 to September 2008 is to study economic growth period of 2004–2005 to 2007–2008. The Lehman Brothers collapse in October 2008 is a major event which resulted in US stock market crash and has almost immediate impact on various Asian economies including India. The rationale of selecting the second period from October 2008 to March 2012 is to study the post-crisis period. The analysis is conducted on stock returns (R_t) and stock volume (V_t) of 1,290 selected BSE stocks for the two periods—April 2004 to September 2008 and October 2008 to March 2012.

The study focuses on monthly observations under the perspective that changes in investor overconfidence occur over monthly or annual horizons (Odean, 1998; Gervais and Odean, 2001; Statman *et al.*, 2006). The monthly data for adjusted closing prices, shares traded, shares outstanding and market capitalization at BSE are collected from Prowess database published by the Centre for Monitoring Indian Economy Pvt Ltd. From the data, two basic variables, stock returns (R_t) and stock volume (V_t) useful for study are developed.

The monthly stock returns are calculated using the formula $R_t = \ln_{pt} - \ln_{pt-1}$. The market return ($R_t$) is computed as the equally weighted index return:

$$R_t = \frac{1}{n}\sum_{i=1}^{N} R_{it}.$$

The turnover is defined as the ratio of the number of shares traded in a month to the number of shares outstanding at the end of the month. The use of turnover is justified by the considerable increases of trades' number. Moreover, one problem with using the number of shares traded as a measure of trading volume is that it is unscaled and, therefore, highly correlated with firm size.

The market descriptive statistics (Table I) for monthly stock returns (R_t) and monthly stock volume (V_t) are studied for an initial understanding of the data and their behavior.

Since both return and turnover series have kurtosis bigger than 3, they are said to have leptokurtic distribution which is more likely to characterize financial time series. In terms of Jarque–Bera statistics, null hypothesis asserting no deviations from normality is tested. Null hypothesis asserting normality is rejected at 5 percent significance level for both return and turnover series. Hence, we can conclude that neither return nor turnover has normal distribution.

Table I.
BSE market descriptive statistics

	Return	Turnover
Mean	0.008678	4.406848
Median	0.024748	2.370387
Maximum	0.384322	43.39540
Minimum	−0.397877	0.714372
SD	0.113322	6.882197
Skewness	−0.425193	3.452048
Kurtosis	4.831857	15.71832
Jarque–Bera	16.31542	837.6887
Probability*	0.000287	0.000000

Note: *Significant at the 5 percent level

The unit root tests are implemented to determine if both time series are stationary because the use of non-stationary variables in analysis causes relations to seem as existing that does not exist in reality. Analysis of non-stationary variables gives biased results of t-test, f-test and R^2 value, in other words it causes spurious regression. Though stationarity of variables could be tested with a variety of methods, Augmented Dickey and Fuller test is implemented for study.

As it could be seen from Table II, null hypothesis asserting unit root has been rejected for returns, whereas it cannot be rejected for stock turnover. This implies that stock turnover has a unit root and non-stationary. Hence, the stock turnover is converted into stationary form by using Hodrick–Prescott algorithm and the detrended turnover series (V_t) is available for further analysis.

4. Hypotheses and empirical methodology

Overconfidence hypothesis contains various implications and, among other things, offers the following empirically testable hypotheses. First, overconfident investors overreact to private information and underreact to public information (*H1*). Second, self-attribution bias, conditioned by right forecasts, increases investors' overconfidence and their trading volume (*H2*). Third, the excessive trading of overconfident investors makes a contribution to the observed excessive volatility (*H3*). In empirically evaluating implications of the overconfidence hypothesis, previous empirical studies tend to focus on the investigation of trading behavior of individual investors and on some specific predictions of the hypothesis. For example, using a sample of discount brokerage accounts, Odean (1999), Barber and Odean (2000, 2001) found that individual investors appear overconfident about their perceived information and ability to trade in that they trade too much.

The main goal of this paper is to provide comprehensive empirical evidence on various implications of the overconfidence hypothesis by focusing on aggregate investor behavior. The focus on aggregate investor behavior is motivated in part by the argument of Odean (1998), Daniel *et al.* (2001) and Gervais and Odean (2001) that investor behavior should be observable in market-level data, and in part by that of Kyle and Wang, Benos (1998), Daniel *et al.* (1998), Hirshleifer and Luo and Wang (2001) that overconfident investors can survive and dominate the markets in the long run. In addition, Fama asserted that a valid finance theory should explain the market as a whole rather than a specific type or group of investors. As such, it is an important empirical issue to examine whether a cognitive bias such as overconfidence is observed in market-level data.

4.1 Overconfidence and differential reaction to information

H1. Overconfident investors overreact to private information and underreact to public information.

	Returns	Turnover
Level—intercept	−8.258958 (−3.500669)	−3.082590 (−3.502238)
Level—trend and intercept	−8.380505 (−4.057528)	−3.335742 (−4.059734)
Level—none	−8.274864 (−2.589531)	−2.474463 (−2.590065)
First difference level—intercept		−6.331535 (−3.503049)
First difference level—trend intercept		−6.309463 (−4.060874)
First difference—none		−6.367408 (−2.590340)
Decision	I(0)	I(1)

Note: Numbers in parentheses are Mckinnon critical values for 1 percent

Table II. Unit root tests for BSE stocks

The first hypothesis stems from the theoretical predictions of overconfidence hypothesis (e.g. Daniel *et al.*, 1998; Odean, 1998). Based on overconfidence and biased self-attribution, Daniel *et al.* (1998) offered a theory in an attempt to explain short-term momentum and long-term reversals. A central theme of their paper is that stock prices overreact to private information and underreact to public information.

To identify private and public information, the methodology presented by Chuang and Lee (2006) is considered. A structural vector autoregression model is employed.

Consider a vector y_t ($y_t = [V_t, R_t]$) consisting of two stationary variables: trading volume V_t and stock return R_t series. Based on the Wold theorem, the vector y_t has a Bivariate Moving Average Representation (BMAR) given by the following relation:

$$y_t \equiv [V_t R_t]' = B(L)\varepsilon_t,$$

or:

$$\begin{vmatrix} V_t \\ R_t \end{vmatrix} = \begin{vmatrix} B11(L)B12(L) \\ B21(L)B22(L) \end{vmatrix} \begin{vmatrix} \varepsilon_t^{private} \\ \varepsilon_t^{public} \end{vmatrix}, \tag{1}$$

where V_t is detrended stock turnover, R_t is stock return, ε_t is a 2×1 vector consisting of $\varepsilon_t^{private}$ and ε_t^{public}, $\varepsilon_t^{private}$ the private information shock, ε_t^{public} is the public information shock, B_{ij} (L) for $i, j = 1, 2$ is the polynomial in lag operator L (i.e. $B_{ij}(L) = \sum_k bij(k)L^k$ with $\sum_k \equiv \sum_{k=0}^{\infty}$), and shocks (or innovations) are orthonormalized such that var (ε_t) is an identity matrix of rank 2.

This representation implies that trading volume and stock returns are driven by two types of shocks: private and public information shocks. The two types of information shocks are distinguished by an identifying restriction imposed on the BMAR model. That is, private information shock $\varepsilon_t^{private}$ has a contemporaneous impact on trading volume, while public information shock ε_t^{public} has no contemporaneous impact on trading volume.

This restriction is motivated by theoretical considerations. Campbell *et al.* (1993) argued that if public information that affects all investors arrives, stock market trading volume may not be significantly affected. Odean (1998) derived in his model that trading volume takes place only when overconfident investors overweight their private information and, as such, form heterogeneous posterior beliefs. Daniel *et al.* (1998) argued that overconfident investors overweight their own private information at the expense of ignoring publicly available information. In light of these arguments, private information plays a more predominant role in triggering trading volume than public information does. The private information is more likely to make investors form heterogeneous beliefs than public information.

The time path of the dynamic effects of the two types of shocks on trading volume and stock returns is represented by coefficients of the polynomial B_{ij} (L). Since b_{12} (k) measures the effect of the second type of shock (ε_t^{public}) on the first variable (V_t) after k periods, the restriction that public information shock (ε_t^{public}) has no contemporaneous effect on trading volume as motivated by several theoretical considerations is represented by the restriction:

$$b_{12}(k)\big|_{k=0} = b_{12}(0) = 0. \tag{2}$$

4.1.1 A restricted bivariate vector autoregression (BVAR) model. The above BMAR on which an identifying restriction is imposed, in practice, is derived by inverting a BVAR model of y_t with non-orthonormalized shocks, and the restriction is imposed on this BVAR model. The restriction on the following BVAR is imposed by following Chuang and Lee (2006).

Suppose that the following BVAR of $y_t = [V_t, R_t]'$ is estimated with p lags:

$$Y_t = \begin{vmatrix} V_t \\ R_t \end{vmatrix} = A(L)y_{t-1} + u_t \equiv \begin{vmatrix} A11(L)A12(L) \\ A21(L)A22(L) \end{vmatrix} \begin{vmatrix} V_{t-1} \\ R_{t-1} \end{vmatrix} + \begin{vmatrix} u_{1t} \\ u_{2t} \end{vmatrix}, \quad (3)$$

where $A(L) = [A_{ij}(L) = [\sum_{k=1}^{p} a_{ij}(k)L^{k-1}]$. for $i, j = 1, 2$, $u_t = [u_{1t}, u_{2t}]' = y_t - E(y_t | y_{t-s}, s \geqslant 1)$, with var $(u_t) = \Omega$. Thus, estimates of $A(L)$ and Ω are known. While ε_t is an orthonormalized shock in y_t with var $(\varepsilon_t) = \mathrm{I}$, u_t is a non-orthonormalized shock in y_t.

Based on the proposition by Chuang and Lee (2006), the bivariate model y_t with the restriction (2) is available to identify $\varepsilon_t^{private}$ and $\varepsilon_t^{\text{public}}$ as private and public information shocks, respectively. The relationship between the BMAR (1) and the BVAR (3) is described in the proposition. Once a restricted BVAR model of trading volume and stock return, $[V_t, R_t]'$, is estimated, we can analyze the stock return responses to private and public information shocks to see whether the responses are compatible with the prediction of overconfidence hypothesis (*H1*).

4.2 Self-attribution and Investors' overconfidence

H2. Self-attribution bias, conditioned by right forecasts, increases investors' overconfidence and their trading volume.

The second hypothesis stems from another central aspect of overconfidence related to finance literature, i.e., the biased self-attribution, the tendency of individuals to attribute good outcomes to their own qualities and bad outcomes to bad luck or other factors. The self-attribution bias is considered by some behavioral models that attempt to provide a theoretical framework for the empirical return anomalies documented in the finance literature (Daniel *et al.*, 1998; Gervais and Odean, 2001). According to Daniel *et al.* (1998) model, investor overconfidence varies because of biased self-attribution which means that when investors receive confirming public information, their confidence level increases; but when they receive disconfirming public information, their confidence level falls only modestly.

On the empirical level, biased self-attribution leads investors to become overconfident after a good past performance (Gervais and Odean, 2001). Consequently, trading volume is greater positively correlated with past stock returns conditional on investors' right forecasts, than that conditional on their wrong forecasts. Indeed, if investors make a right forecast, i.e., if they predict positive stock returns at time t–1 and realized stock returns are positive at time t, then their overconfidence rises significantly, and consequently they trade more actively in subsequent periods. If, on the other hand, investors make a wrong forecast, i.e., if they predict negative stock returns at time t–1 and realized stock returns are positive at time t, then their overconfidence may fall only modestly because they still benefit from market gains (Chuang and Lee, 2006).

To investigate how these two factors separately and simultaneously affect investors' overconfidence and their trading behavior, stock returns are decomposed into expected returns and unexpected returns by employing EGARCH-type specifications, taking into account an asymmetric effect in which a negative return shock increases volatility more than does a positive return shock (i.e. the leverage effect).

The study considers Nelson's Exponential GARCH (EGARCH(1, 1)) model:

$$Rt = \mu_t + \eta_t,$$

$$\eta_t | (\eta_t - 1, \eta_t - 2, \ldots) \sim GED(0, h_t),$$

$$\ln(h_t) = \omega + \beta \log(h_t - 1) + \gamma \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\left| \frac{\eta_{t-1}}{\sqrt{h_{t-1}}} \right| - \sqrt{2/\pi} \right],$$

where R_t is the stock return, μ_t is the mean of R_t conditional on past information and h_t is the conditional volatility. The asymmetric effect in the EGARCH model is captured by the volatility parameter γ. If $\gamma < 0$, then the conditional volatility tends to increase (decrease) when the standardized residual is negative (positive).

To allow for the possibility of non-normality in the conditional distribution of stock returns, for example, one having fatter tails than the normal distribution, the study assumes that the conditional errors of the EGARCH specifications follow a generalized error distribution.

To study the dynamic contribution of self-attribution bias to investor overconfidence, the study proposes the following regression model:

$$V_t = \alpha_0 + \alpha_1|R_t| + \alpha_2 MAD_t + \alpha_3 R_t + \sum_{j=1}^{P} \beta_j \mu_{t-j} + \varepsilon_t, \tag{4}$$

where μ_t is the expected returns derived from the EGARCH specifications. In above equation, the $\chi^2_{\beta(1)}$ and $\chi^2_{\beta(2)}$ test statistics, obtained from the Wald test, are used for testing the null hypothesis that $\sum_{j=1}^{P} \beta_j = 0$ and the null hypothesis that $\beta_j = 0$ for all j, respectively. The statistical significance of the $\chi^2_{\beta(1)}$ and $\chi^2_{\beta(2)}$ test statistics is indicative of evidence that investors are subject to self-attribution bias.

To examine whether investor overconfidence associates with unpredictable events, the study considers the following regression model:

$$V_t = \alpha_0 + \alpha_1|R_t| + \alpha_2 MAD_t + \alpha_3 R_t + \sum_{j=1}^{P} \gamma_j \eta_{t-j} + \varepsilon_t, \tag{5}$$

where η_t is the unexpected returns derived from the EGARCH specifications. In above equation, the $\chi^2_{\gamma(1)}$ and $\chi^2_{\gamma(2)}$ test statistics, yielded from the Wald test, are used for testing the null hypothesis that $\sum_{j=1}^{P} \gamma_j = 0$ and the null hypothesis that $\gamma_j = 0$ for all j, respectively. The rejection of both null hypotheses provides evidence consistent with conjecture that unpredictable shocks impact investor overconfidence.

Finally, in an attempt to investigate the simultaneous effects of self-attribution bias and unpredictability on investor overconfidence, the study estimates the following regression model:

$$V_t = \alpha_0 + \alpha_1|R_t| + \alpha_2 MAD_t + \alpha_3 R_t + \sum_{j=1}^{P} \beta_j \mu_{t-j} + \sum_{j=1}^{P} \gamma_j \eta_{t-j} + \varepsilon_t, \tag{6}$$

where μ_t and η_t are the expected and unexpected returns, respectively, derived from the EGARCH specifications. In above equation, the $\chi^2_{\beta(1)}$ and $\chi^2_{\beta(2)}$ test statistics, obtained from the Wald test, are used for testing the null hypothesis that $\sum_{j=1}^{P} \beta_j = 0$ and the null hypothesis that $\beta_j = 0$ for all j, respectively, and designed to examine the effects of self-attribution bias on investor overconfidence in the presence of unpredictable shocks. Likewise, the $\chi^2_{\gamma(1)}$ and $\chi^2_{\gamma(2)}$ test statistics, yielded from the Wald test, are used for testing the null hypothesis that $\sum_{j=1}^{P} \gamma_j = 0$ and the null hypothesis that $\gamma_j = 0$ for all j, respectively, and devised to examine the impacts of unpredictable shocks on investor overconfidence in the existence of self-attribution bias. Furthermore, if unpredictable shocks, for example, play a predominant role in increasing investor overconfidence, then it is expected to see that $\sum_{j=1}^{P} \gamma_j > \sum_{j=1}^{P} \beta_j > 0$ and that the $\chi^2_{\gamma(1)}$

test statistics is greater than the $\chi^2_{\beta(1)}$statistic. Another formal test statistic, $\chi^2_{\beta\gamma}$, is utilized to test the null hypothesis that$\sum_{j=1}^{P} \beta_j = \sum_{j=1}^{P} \gamma_j$.

Motivated by previous studies, absolute returns i.e., $|R_t|$ and mean absolute cross-sectional return deviation, i.e., MAD_t are used as control variables in Equations (4)–(6). For example, Karpoff (1987) reviewed and discusseed empirical findings of a positive contemporaneous relation between trading volume and the volatility of stock returns from a variety of theoretical perspectives. Therefore, it is reasonable to include the absolute value of stock return to control this contemporaneous relation. Ross showed that in a frictionless market characterized by an absence of arbitrage opportunities, the rate of information flow is revealed by the degree of price volatility. Based on this intuition, Bessembinder *et al.* (1996) used $|R_t|$ to proxy for common information flow and MAD_t for firm-specific information flow in order to account for informational trades. Furthermore, Harris and Raviv (1993) showed that trading is generated by differences of opinion among traders in their interpretations of public information regarding the value of the asset being traded and demonstrated that volume and absolute price changes are positively correlated. As a result, $|R_t|$ and MAD_t can capture trading resulting from the variety of opinions among investors as public information is revealed in stock market[3].

4.3 Overconfidence and volatility

H3. The excessive trading of overconfident investors makes a contribution to the observed excessive volatility.

The third hypothesis reflects the view of previous studies that there is a relationship between volatility and trading volume (Lamoureux and Lastrapes, 1990; Schwert, 1989; Benos, 1998). Odean (1998) and Gervais and Odean (2001) showed that the volatility is increasing in a trader's number of past success and thereby in a level of investors' overconfidence. Overconfidence has been advanced as an explanation by these studies for the observed excessive volatility. The objective of testing this hypothesis empirically is to distinguish excessive trading volume of overconfident investors from other factors that affect volatility.

The study begins by employing the following regression to decompose trading volume into two components:

$$V_t = \alpha + \sum_{j=1}^{P} \hat{\beta}_j R_{t-j} + \varepsilon_t = \text{OVER}_t + \text{NONOVER}_t, \tag{7}$$

The constant and residual terms in the above equation are defined as the component of trading volume unrelated to investors' overconfidence (NONOVER_t), and the difference between trading volume and the constant and residual terms as the component of trading volume associated with investors' overconfidence due to past stock returns (OVER_t). These two components of trading volume are then incorporated into the conditional variance equation of the EGARCH model(s) that are developed using ARMA (p, q) terms to fit the data for BSE stocks:

$$\begin{gathered} R_t = \mu_t + \eta_t, \\ \eta_t \left| (\eta_t - 1, \eta_t - 2, \ldots) \sim GED(0, h_t), \right. \\ \ln(h_t) = \omega + \beta \log(h_t - 1) + \gamma \frac{\eta_t - 1}{\sqrt{h_t - 1}} + \alpha \left[\left| \frac{\eta_t - 1}{\sqrt{h_t - 1}} \right| - \sqrt{2/\pi} \right] + \delta_1 \text{OVER} + \delta_2 \text{NONOVER}. \end{gathered} \tag{8}$$

The empirical framework of Equations (7) and (8) will allow distinguishing excessive trading of overconfident investors from other factors that affect market volatility. For example, the "differences of opinion" model of Harris and Raviv (1993) predicts that volatility is positively correlated with trading volume. They provide a model of speculative trading volume and price dynamics. They have assumed that traders receive common information (public information announcements) but differ in the way in which they interpret this information, and each trader believes absolutely in the validity of his or her interpretation. They refer to this as the assumption that traders have "differences of opinion." They demonstrate that the trading is generated because of "differences of opinion" among traders regarding the value of the asset being traded (Harris and Raviv, 1993). Therefore, δ_1 parameter works to capture the overconfidence effect on volatility, while the δ_2 parameter is designed to capture other potential explanations of excessive volatility. The statistical significance of the estimated δ_1 parameter, coupled with observation that $\delta_1 > \delta_2$, indicates that the overconfidence component of trading volume is positively correlated with market volatility, which implies that high market volatility can be partially justified on the ground of investors' overconfidence. Moreover, the statistical significance of the estimated δ_2 parameter suggests that overconfidence is not a unique cause of high market volatility but other interpretations such as the "difference of opinion" hypothesis are also responsible for the observed market volatility. Z-statistic is used to test the null hypothesis that $\delta_1 = \delta_2$. The α parameter is typically interpreted as "news" (shocks) coefficient that measures the impact of recent news on volatility whereas β parameter measures the persistence in conditional volatility irrespective of anything happening in the market. The γ parameter captures the "leverage effect," i.e., the negative return shock increases volatility more than does a positive return shock of the same magnitude in the market.

5. Empirical results

5.1 Overconfidence and differential reaction to information

To estimate the BVAR of y_t, the number of lags have to be chosen. Akaike information criterion is used to decide on the lag length. The study investigates, by plotting moving average coefficients, $b_{ij}(k)$, how each type of shock affects stock prices over various horizons. Figures 1 and 2 present the dynamic responses, measured in standard deviations, of stock

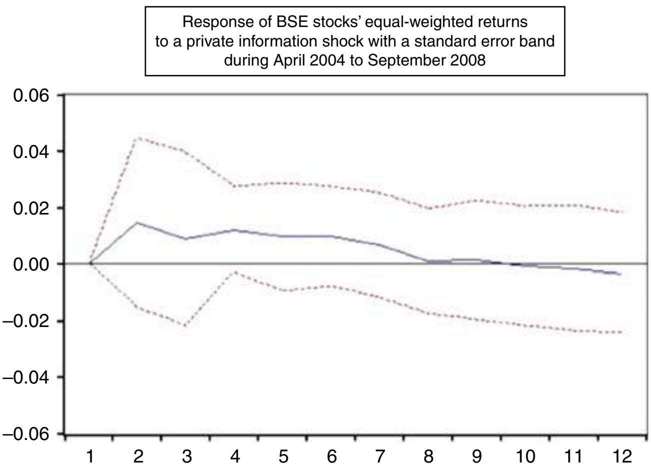

Figure 1.
Response of BSE stocks price to private information shocks during April 2004 to September 2008

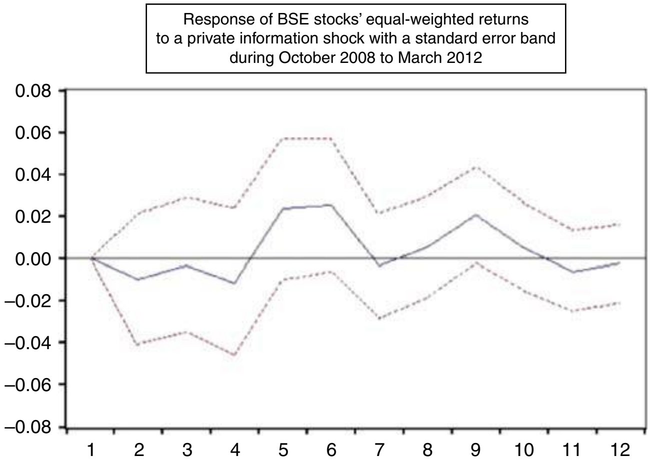

Figure 2. Response of BSE stocks price to private information shocks during October 2008 to March 2012

prices to 1 standard deviation shock in ($\varepsilon_t^{private}$) and (ε_t^{public}) over the 12 periods. It includes 1 (conditional) standard error band around the mean response.

Figure 1 shows that equal-weighted stock prices strongly overreact to a private information shock. After persistent increase, there is a correction process during tenth period wherein equal-weighted stock prices reach their equilibrium response to a private information shock. The pattern of this impulse-response function is compatible with the prediction of models proposed by Daniel *et al.* (1998) and Odean (1998). This observation is also compatible with the results of Daniel and Titman showing that stock prices overreact to intangible information, which is unrelated to accounting-performance measures if one interprets private information in terms of intangible information. Whereas Figure 2 shows that equal-weighted stock prices initially move around the mean followed by strong overreaction to a private information shock starting from fifth period. After such increase, there is a correction process after which equal-weighted stock prices reach their equilibrium response to a private information shock.

Figures 3 and 4 show that equal-weighted stock prices initially underreact to a public information shock and then quickly reach the equilibrium response to a public information shock, suggesting short-term momentum. The observations of response of stock price to public information is consistent with the expectation of the overconfidence hypothesis and compatible with findings of Daniel and Titman, who demonstrated that stock prices do not overreact to tangible information, which is directly related to accounting-growth measures.

It is understood from the analysis that investors at BSE strongly overreact to private information and underreact to public information signifying long-term reversal and short-term momentum in the market. These patterns of impulse-response function are compatible with the prediction of models proposed by Daniel *et al.* (1998) and the study conducted by Chuang and Lee (2006).

5.2 Self-attribution and investors' overconfidence

In an attempt to investigate the independent and simultaneous effects of self-attribution bias and unpredictability on investor overconfidence, the study estimates EGARCH models for BSE stocks. The econometric models are improvised, wherever required, to an extent where Durbin–Watson statistic and Ljung–Box statistic indicate no potential misspecification problem. The output generated from such improvised and appropriate models is presented

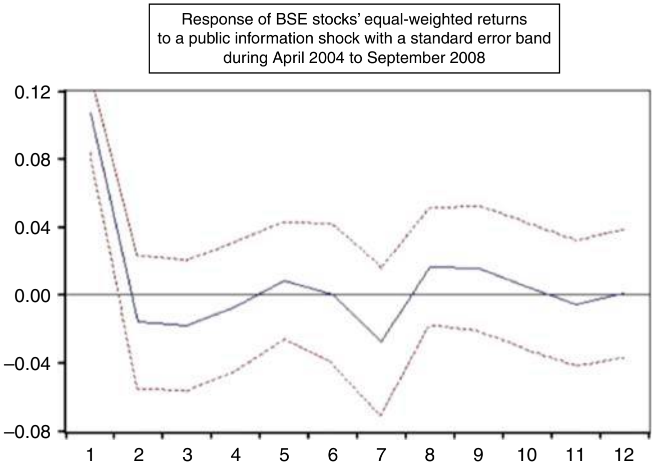

Figure 3. Response of BSE stocks price to public information shocks during April 2004 to September 2008

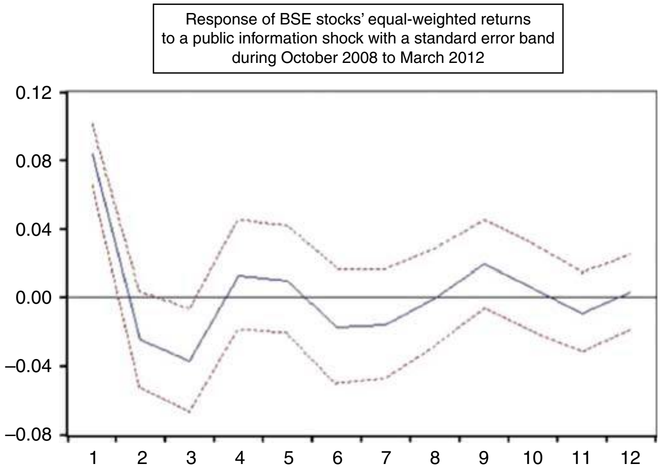

Figure 4. Response of BSE stocks price to public information shocks during October 2008 to March 2012

in Tables III–V to understand the relationship between trading volume and expected returns, return shocks and components of stock returns, respectively.

From Tables III and IV, it is understood that the results are consistent with the concept of self-attribution bias that investors trade more aggressively after their overconfidence rise due to the fact that they successfully predict stock prices. The findings support the accumulated evidence from the studies conducted by Daniel *et al.* (1998), Gervais and Odean (2001), Chuang and Lee (2006), Feng Li (2010). On the other hand, it is also understood that the trading volume is positively related to the past unexpected returns. This is in line with the psychological argument that overconfidence increases with the extent of unpredictability of events (De *et al.*, 2011; Prosad *et al.*, 2015).

With respect to simultaneous effects of self-attribution bias and unpredictability on investor overconfidence, it is understood from Table V that $\sum_{j=1}^{P} \gamma_j > \sum_{j=1}^{P} \beta_j > 0$ during both the periods. On the other hand, $\chi^2_{\gamma(1)}$ is greater than the $\chi^2_{\beta(1)}$ and is also significant during April 2004 to September 2008 which indicates that the trading volume is positively

Source of μ_t and n_t ARMA(1, 1)–EGARCH(1, 1) Dependent Variable—V_t	April 2004 to September 2008			October 2008 to March 2012		
Independent variable	Coefficient	t-Statistic	Prob.*	Coefficient	t-Statistic	Prob.*
α_0	1.0599	2.1926	0.0351	2.5673	5.1834	0.0000
α_1	−0.5603	−0.8969	0.3759	0.1871	0.1360	0.8931
α_2	0.7775	0.3105	0.7580	−5.1579	−0.7926	0.4365
α_3	0.2440	0.7498	0.4584	0.6942	1.1279	0.2715
β_1	1.5457	1.2030	0.2370	3.6384	3.1238	0.0049
β_2	3.3233	1.8428	0.0738	8.0387	5.0444	0.0000
β_3	4.2986	2.3784	0.0230	11.3895	6.0440	0.0000
β_4	4.7195	2.6412	0.0123	11.6520	6.5006	0.0000
β_5	4.8440	2.7386	0.0096	8.9379	5.8457	0.0000
β_6	3.1189	2.1607	0.0377	5.2221	4.0350	0.0006
β_7				2.5028	2.5338	0.0189
λ_1	1.0113		0.0003			
Summation of β-coefficients	21.8501			51.3814		
$\chi^2_{\beta(1)}$	13.0226		0.0003	61.2092		0.0000
$\chi^2_{\beta(2)}$	13.6894		0.0333	63.5830		0.0000
R^2	0.9877			0.8074		
DW	2.4501			1.9941		
$Q(2)$	6.1713		0.0460	0.1523		0.9270
$Q(4)$	6.2055		0.1840	5.9006		0.2070
$Q^2(2)$	1.0116		0.603	0.3318		0.847

Note: *Significant at the 5 percent level

Table III. Relationship between trading volume and expected returns for BSE stocks

Source of μ_t and n_t ARMA(1, 1)–EGARCH(1, 1) Dependent variable—V_t	April 2004 to September 2008			October 2008 to March 2012		
Independent variable	Coefficient	t-Statistic	Prob.*	Coefficient	t-Statistic	Prob.*
α_0	0.1342	0.4233	0.6746	1.8442	4.5354	0.0001
α_1	−0.1354	−0.2184	0.8283	1.3972	1.3754	0.1817
α_2	−1.0618	−0.3601	0.7208	−2.0868	−0.3739	0.7117
α_3	0.3726	1.2051	0.2358	1.1852	2.8976	0.0079
γ_1	0.4441	1.2824	0.2077	1.5390	3.7729	0.0009
γ_2	0.7253	2.1982	0.0343	2.0961	4.7169	0.0001
γ_3	0.6258	2.0678	0.0457	1.4963	3.8200	0.0008
γ_4	0.5416	1.7530	0.0879	0.6859	1.8349	0.0790
γ_5	0.5890	1.9276	0.0616	0.9651	2.6192	0.0150
γ_6	0.4233	1.2374	0.2237	1.1591	3.1663	0.0042
γ_7				0.5553	1.5326	0.1385
λ_1	0.9985	53.1195	0.0000			
Summation of γ-coefficients	3.3491			8.4968		
$\chi^2_{\gamma(1)}$	14.8358		0.0001	67.4442		0.0000
$\chi^2_{\gamma(2)}$	15.4042		0.0173	70.0629		0.0000
R^2	0.9882			0.8432		
DW	1.924469			1.8300		
$Q(2)$	0.1941		0.9080	0.5425		0.7620
$Q(4)$	5.0241		0.2850	0.5528		0.9680
$Q^2(2)$	0.1043		0.949	1.079		0.583

Note: *Significant at the 5 percent level

Table IV. Relationship between trading volume and return shocks for BSE stocks

Table V. Relationship between trading volume and the components of stock returns

Source of μ_t and n_t ARMA(1, 1)–EGARCH(1, 1) Dependent variable—V_t	April 2004 to September 2008			October 2008 to March 2012		
Independent variable	Coefficient	*t*-Statistic	Prob.*	Coefficient	*t*-Statistic	Prob.*
α_0	0.1162	0.3185	0.7517	0.2433	0.3895	0.6997
α_1	−0.0209	−0.0324	0.9743	−2.2355	−1.3292	0.1938
α_2	−0.4305	−0.1496	0.8818	21.0285	2.5087	0.0178
α_3	0.5058	1.5536	0.1280	1.0990	1.4450	0.1588
β_1	−0.1278	−0.0676	0.9464	−2.9259	−1.5096	0.1416
β_2	0.6448	0.5159	0.6087	−0.0402	−0.0308	0.9756
γ_1	0.5285	1.4976	0.1419	0.0523	0.0716	0.9434
γ_2	0.7119	1.2776	0.2086	1.9190	1.8394	0.0758
λ_1	0.9937	51.1566	0.0000			
Summation of β-coefficients	0.5169			−2.9661		
$\chi^2_{\beta(1)}$	0.0312		0.8598	1.1219		0.2895
$\chi^2_{\beta(2)}$	0.6820		0.7110	2.8750		0.2375
Summation of γ-coefficients	1.2405			1.9713		
$\chi^2_{\gamma(1)}$	3.4758		0.0623	2.1855		0.1393
$\chi^2_{\gamma(2)}$	3.8023		0.1494	3.3970		0.1830
R^2	0.9862			0.4741		
$\chi^2_{\beta\gamma}$	0.0484		0.8259	2.0503		0.1522
DW	1.875361			2.0558		
$Q(2)$	0.0791		0.9610	0.7866		0.6750
$Q(4)$	1.5529		0.8170	1.8612		0.7610
$Q^2(2)$	1.8535		0.396	0.1777		0.915

Note: *Significant at the 5 percent level

related to the combined past unexpected returns. It is understood from the analysis that the unpredictability of events plays a more predominant role in strengthening investors' overconfidence than does the impact of self-attribution bias when both co-exist during April 2004 to September 2008 and the impact of both is offset during October 2008 to March 2012 (De *et al.*, 2011; Prosad *et al.*, 2015).

5.3 Overconfidence and volatility

The conditional volatilities based on the ARMA(2, 2)–EGARCH(1, 1) model are estimated for both the first and second periods of the study as follows:

$$R_t = \alpha_0 - \beta_1 R_t - 1 - \beta_2 R_t - 2 + \gamma_1 \eta_t - 1 + \gamma_2 \eta_t - 2 + \eta_t,$$

$$\eta_t \big| \left(\eta_t - 1, \eta_t - 2, \ldots\right) \sim GED(0, h_t),$$

$$\ln\left(h_t\right) = \omega + \beta \log\left(h_t - 1\right) + \gamma \frac{\eta_t - 1}{\sqrt{h_t - 1}} + \alpha\left[\left|\frac{\eta_t - 1}{\sqrt{h_t - 1}}\right| - \sqrt{2/\pi}\right] + \delta_1 \text{OVER} + \delta_2 \text{NONOVER}$$

The two components (OVER_t and NONOVER_t) of trading volume are incorporated into the conditional variance equation to identify whether the observed excessive volatility results from excessive trading due to overconfident investors. The results of the analysis performed are presented in Table VI.

The parameter δ_1 represents the measure of overconfidence effect (overconfidence or OVER_t) on volatility whereas the δ_2 measures the effect of other potential factors (non-overconfidence or NONOVER_t) on excessive volatility. The statistical significance of

Model	ARMA(2, 2)–EGARCH(1, 1)					
Conditional volatility	$\ln h_t$					
Trading volume	V_t					
	April 2004 to September 2008			October 2008 to March 2012		
Parameter	Coefficient	*Z*-statistic	Prob.*	Coefficient	*Z*-statistic	Prob.*
Conditional mean equation						
α_0	0.0351	6.8270	0.0000	0.0187	1.0453	0.2959
β_1	−1.3224	−13.9140	0.0000	−0.6826	−3.4687	0.0005
β_2	−0.7914	−11.3372	0.0000	−0.7825	−3.0186	0.0025
γ_1	1.4726	19.9508	0.0000	0.7858	3.7146	0.0002
γ_2	0.8632	17.0195	0.0000	0.7831	3.2169	0.0013
Conditional variance equation						
ω	−1.3224	−1.5937	0.1110	−1.6189	−1.3999	0.1615
β	1.8708	3.8228	0.0001	−0.9371	−1.5121	0.1305
γ	0.4491	1.5305	0.1259	−0.1957	−0.6050	0.5452
α	0.8109	5.9408	0.0000	0.6581	3.0770	0.0021
δ_1	0.9265	1.6482	0.0993	1.6714	0.6477	0.5172
δ_2	−0.1759	−1.4275	0.1534	0.2716	1.1644	0.2443
Log likelihood	60.93071			56.2514		
Standard residual diagnostics						
$Q(5)$	2.9804		0.084	14.161		0.0000
$Q(8)$	7.6821		0.104	16.44		0.0020
$Q(12)$	9.7361		0.284	16.948		0.0310
$Q^2(5)$	8.7101		0.003	2.4892		0.1150
$Q^2(8)$	11.294		0.023	3.7485		0.4410
$Q^2(12)$	14.815		0.063	5.3945		0.7150
$Q^2(14)$	15.816		0.105			
Z-statistic	3.397942		0.0653	0.27293		0.6014
Joint sign test	6.440356		0.092	5.261439		0.1536
Sign bias test	1.73E-05		0.9967	1.63E-01		0.6865
Size bias test	5.477597		0.0646	5.002312		0.082

Note: *Significant at the 5 percent level

Table VI. Relationship between the conditional volatility of stock returns and trading volume

the estimated δ_1 parameter, coupled with $\delta_1 > \delta_2$, during April 2004 to September 2008 indicates that the overconfidence component of trading volume is positively correlated with market volatility. This implies that the high market volatility during April 2004 to September 2008 can be partially justified on the ground of investors' overconfidence. The findings are compatible with the observations made by Daniel *et al.* (1998), Odean (1999), Barber and Odean (2000, 2001), Chuang and Lee (2006), De *et al.* (2011) and Prosad *et al.* (2017). However, there is no evidence for investors' overconfidence behavior during October 2008 to March 2012. During this period, there could be "differences of opinion" among traders regarding the value of asset being traded as proposed by Harris and Raviv (1993).

6. Conclusion and implications

There is a growing literature showing that the overconfidence bias is useful for explaining many asset-pricing anomalies. This is the first paper which provides empirical evaluation of investors' overconfidence behavior at market-level data consisting of all stocks traded at BSE during study period.

The analysis of the returns impulse responses to the private and public information shocks shows that the returns overreact to private information and underreact to public information. Price behavior of all BSE stocks during both the periods of study is in favor of first hypothesis that overconfident investors overreact to private information and underreact to public information which is the central theme of overconfidence hypothesis proposed by Daniel *et al.* (1998).

Next, the investors' reaction to market gain when they make right and wrong forecasts is studied to understand whether self-attribution bias causes investor' overconfidence. Investors' forecasts of future stock returns and forecast errors are derived from two EGARCH specifications that allow for asymmetric shocks to volatility. Overall, it is found that when investors make right forecasts of future returns, they become overconfident and trade more in subsequent time periods. On the other hand, when they make wrong forecasts, their overconfidence may fall modestly. This finding provides empirical evidence in support of the second hypothesis during both the periods of study that self-attribution bias, conditioned by right investors' forecasts, increases their overconfidence and their trading volume. The results are compatible with the findings of Daniel *et al.* (1998) and Chuang and Lee (2006).

Finally, the relation between excessive trading volume of overconfidence investors and excessive prices volatility is studied. The trading volume is decomposed into a first variable related to overconfidence and a second variable unrelated to investors' overconfidence. The analysis of the relation between return volatility and these two variables shows that conditional volatility is positively related to trading volume caused by overconfidence during April 2004 to September 2008. The results are compatible with the findings of Daniel *et al.* (1998), Chuang and Lee (2006) and Prosad *et al.* (2017). There is no statistical evidence for overconfidence behavior during post-crisis period, i.e., October 2008 to March 2012. This could be because of the global crisis impact on the investor sentiment lowering their level of confidence in stock markets behavior (Prosad *et al.*, 2015).

Overall, the detailed observation of findings and conclusions made for each and every objective of the study reveals that the investors are subjected to biased self-attribution and overconfidence. They trade aggressively following high stocks returns. They also overreact to private information shocks because of their persistent belief that the precision of their own private signals about asset fundamentals is higher than it really is. Generally, the results provide strong statistical support to the presence of overconfidence bias among investors at BSE.

6.1 Implications of the study

The overall Indian stock market is affected, if investors suffer from behavioral biases. Overconfidence bias is considered to be the most prevalent bias by various studies. Markets that suffer from overconfidence bias tend to have extreme reactions. Overconfidence is one of the most detrimental biases that an investor can exhibit. This is because of underestimating downside risk, trading too frequently and/or trading in pursuit of the "next hot stock," and holding an under-diversified portfolio. All these pose serious hazards to one's wealth. Especially, the overconfidence is trying to time the market and trade aggressively following high stocks returns.

The findings of the study have significant managerial implications for different stakeholders such as individual investors, fund managers and asset management companies, policy makers and academic community.

6.1.1 Implications for investors. By knowing that a particular bias prevails in the market will not help the investors in making any practical strategies. Success often comes from restraining the emotions and overcoming behavioral biases. They should perform a post-analysis of each investment so that they become aware of past behavioral mistakes and stop continuing the same. Particularly, they should review unprofitable decisions and look for patterns or common mistakes that perhaps they were unaware of making. Investors also need to invest for the long term, identify their level of risk tolerance, determine an appropriate asset allocation strategy and rebalance portfolios frequently. This might help investors to minimize the negative impact of self-attribution and overconfidence on their expected utility. As Glaser and Weber suggested that this counter attack on behavioral biases or "de-biasing" can be made with the help of behavioral training and increasing financial literacy.

6.1.2 Implications for fund managers and asset management companies. It is recommended that the fund managers and asset management companies should try to identify behavioral biases in their clients before designing their portfolios. Investors overreact to private information signals and underreact to public information signals. This is then followed by long-run correction. By understanding this relationship and analyzing the hidden trends in trading volume and returns, fund managers can identify the specific stocks which are prone to these behavioral biases for which extra caution is required. Such knowledge can help them in developing strategies and taking appropriate measures. They also have to be very careful about the volatility based trading strategies in pursuit of profitability. Both the fund managers and asset management companies have to "de-bias" themselves by applying proper knowledge and making rational investment decisions in order to avoid a "wealth loss" situation for both investors and themselves.

6.1.3 Implications for policy makers. There are some policy implications for an emerging market like India which is yet to achieve the depth and width of a developed market. There is a need for a deeper knowledge of the reasons for stock market returns, its volatility, foreign institutional investments and their rapidly changing composition. With international investors investing globally, markets have become more integrated and their switching of funds between different markets has led to increased volatility in some markets. So it is quite possible that Foreign Institutional Investors (FIIs) have contributed to excessive market volatility in Indian stock markets. However, there are three policy implications. First, the domestic investor base has to be strengthened because the stock market participation by majority of savers in India is quite low. This may be achieved through the harmonization of corporate governance, accounting and listing, as well as other standard rules and practices. Second, policy makers are suggested to manage short term, non-debt creating flows to emerging economies in a pragmatic and improved manner. Third, there should be a constant watch on FIIs, especially for their regular selling activities at the time of crisis when the outflow is more than inflow, as to tackle the persistent stock market volatility to a great extent.

6.1.4 Implications for academic community. For the academic community, the study provides several results which are consistent with prior literature on self-attribution and overconfidence behavior. It further confirms that the self-attribution leads investors to become overconfident after a good past performance (Gervais and Odean, 2001). This is the first study to provide empirical evidence for the behavioral biases (i.e. self-attribution and overconfidence) at a market level considering all the listed stocks on BSE. This study can be helpful in providing an insight into the prevailing behavioral biases in the Indian stock market. The study contributes to the areas of excessive volatility, self-attribution and overconfidence for emerging markets such as India. However, the future research can study various behavioral biases based on daily data and delve deeper as to whether they are significant in creating inefficiencies in the Indian stock markets and across different global market settings.

Notes

1. For example, Fama, Daniel *et al.* (1998) reviewed the literature on those anomalies. Daniel *et al.* (2002), Heaton and Korajczyk discussed those anomalies.

2. Barberis *et al.* offered a model of investor sentiment based on two assumptions of cognitive bias: conservatism and representative heuristic, while Daniel *et al.* (1998) developed a theory relied on alternative assumptions of cognitive bias: overconfidence and biased self-attribution. Gervais and Odean (2001) proposed a multiperiod market model showing how a learning bias can create overconfident traders.
3. Bessembinder *et al.* (1996) used futures' open interest proxy for divergences of traders' opinion and find that both $|R_t|$ and MAD_t highly positively correlated with futures' open interest.

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