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INVESTORS' OVERCONFIDENCE IN THE STOCK MARKET

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Abstract: An investor would normally depend on technical or/and fundamental analysis to make his/her investment decision in the secondary market. But in most cases the investor may not have time to do these analyses, understand the market or stock and then make the decision, therefore, they often end up taking irrational decisions. In some cases, the investors take these irrational decisions on the basis of the overconfidence they have concerning the information they possess. These investors are termed to bear overconfidence bias. The study aims to examine the influence of overconfidence bias in the Indian stock market. The study employed Vector Autoregression (VAR) methodology and impulse response function to know how long the bias persists in the market once the overconfidence bias is influenced by the investor. The results of the study show enough evidence to point out the influence of overconfidence bias in the market and it persists for more than 110 days. The study also finds that Efficient Market Hypothesis does not hold good. Our study period includes the time period since globalization of the Indian stock market and it also covers several periods of stress including the global financial crisis of 2007–08 and COVID-19 period.

Introduction

An astute investor will predict the movement of price of stocks accurately and should be an expert in the selection of such stocks. An investor who is confidently executing these decisions would rely upon technical and fundamental analysis for stock selection. However, realistically, an investor has to take such decisions in a very short span of time and often it would be difficult to thoroughly analyse before making these trading decisions. Hence, they can rely on quick analysis and can end up with decisions that are irrational. Some investors are overconfident in taking such decisions because of the overconfidence concerning the accuracy of the information they possess. These investors who are under the influence of such biases are called overconfident investors or possess overconfidence bias. Studies have brought out much irrationality prevalent in investor trading. Bondt and Thaler (1985); Bondt and Thaler (1987); and Lee, Shleifer and Thaler (1991) show that investors 'overreact' to unexpected and dramatic market events.

Overconfidence bias is a psychological bias defined as an excessive belief in one's intuitive reasoning, judgements and cognitive abilities (Pompian, 2008). The lack of knowledge results in irrational decision making by the investors who are often clouded by behavioural biases like overconfidence bias. Psychologists have identified two types of overconfidence bias; namely, prediction overconfidence bias and certainty overconfidence bias. A trade needs to be preceded by prediction of future price of stocks and followed by judicious selection of stocks to buy and sell. Investors with prediction overconfidence bias do not allow a leeway of more than ten percent deviation in the future price while certainty overconfidence bias makes them too certain of their choice of stocks and time to trade (Pompian, 2008). Both biases entail more than average risk and eventually investors with overconfidence bias are bound to suffer losses.

According to the overconfidence bias, a trader at the start of their career is not overconfident. During the course of trading when he/she initially meets with success and becomes wealthier, the biased learning makes him/her overconfident (Odean, 1999; Gervais & Odean, 2001). Success boosts his/her trading activity and he/she begins to suffer losses or reduced returns. With experience they discover the true potential and limitations of their analyses, and consequently, their confidence decreases. At any point in time the market will always have some investors with overconfidence bias which makes the market buoyant and irrational. It is this irrationality that has been one of the root causes of recurring market bubbles and crashes, causing huge loss to investors and economies. Hence, the study of behavioural biases in financial markets continues to be an active topic of study by academicians and of interest to all market stakeholders.

Our study examines the presence of overconfidence bias in the stock market using Vector Autoregression (VAR) model and finds the persistence of this bias using impulse response functions. The VAR model is applied by taking log value of trading volume and log value of market return as dependent variable and log value of volatility, lag value of log trading volume and lag value of log market return as independent variables. In addition to that, the present study also covers the COVID-19 phase. Thus, the study period is from 1st April 2005 to 31st March 2022 (17 financial years) covering several ups and down. This makes the study more attractive to the practitioners and investors in knowing the behaviour of investors and their confidence level. We find the presence of overconfidence bias in the market and these effects persist for more than 110 days.

The paper is organised as follows: the background of the study and the related papers are discussed in Section 2, Section 3 describes the data and methodology part of the study and formulates the study Hypothesis, Section 4 describes the study results, and in Section 5 we conclude.

Background of the study

Market anomalies are quite common when the illusionary investors are overconfident to predict the future price movements. There are several studies that have brought out the salient features of overconfidence bias. A study of trading behaviour of 215 investors who believe they have more than average investment skill has shown a higher than average number of trading due to the effect of overconfidence bias (Glaser & Webber, 2007). The study also shows that contrary to the theory, miscalibration is not related to trading volume, which indicates that higher trading is almost uniquely related to overconfidence bias. There are now several studies which establish a positive relationship between trading volume and overconfidence bias (Statman, Thorley & Vorkink, 2006; Koutmos & Song, 2014). In Japanese stock market, the pattern of investment followed by various types of investors, i.e., individual investors, foreign investors and institutional investors reveals that the performance of individual investors has proved to be poor and others good in comparison. The results also produced evidence for the influence of both information based trading and behavioural based trading exists in the market at the same time (Kamesaka, Nofsinger & Kawakita, 2003). These studies highlight the two most important and observable features of overconfidence bias, namely, more than average trading frequency, and consequently, less than average returns. Besides this, the study also provides evidence that investing culture in Asian economies is more prone to overconfident bias than other economic cultures.

There are studies which show how strongly overconfidence bias influences investors. Overconfidence bias tempts investors to trade in directions opposite to market trends because of their false faith in the special knowledge they possess (Daniel, Hirshleifer & Subrahmanyam, 1998 and Odean, 1998a). Overconfident investors assume they are capable of selecting the best time to buy and sell off assets to get maximum return (Pompian, 2008). But their frequent trading and overconfidence results in lower profit than other investors because of their overestimation of the precision of information they possess. This has been confirmed in an experimental study of overconfidence bias wherein risk aversion was induced. The study shows that overconfident investors do not pay any attention to other important market information which results in decisions far removed from optimum market situations. The deviation from the optimal decision positively correlates with the increase in the level of overconfidence (Dittrich, Güth & Maciejovsky, 2005). Non-optimal decisions increase underestimation of associated risks and cause overconfident investors to trade more in riskier securities (Chaung & Lee, 2006). The riskier trading always results in reduced returns for their investments. This link between overconfidence among investors consequently increases their trading frequency, and the resultant decrease in expected utility, when compared with normal investors, has been proved beyond doubt (Odean, 1998a). Reverses in trading do not deter overconfident investors and they continue to trade with the same strategy. A detailed study on investments in US during the period from 1991 to 1997 has also shown that excessive trading results in reduction in annual returns (Barber & Odean, 2001).

Vector Auto Regression (VAR) model has been used with great success to study overconfidence bias in markets across the world. A study in the US during the period from January 1963 to December 2001 inspected the presence of overconfidence bias in the New York Stock Exchange by using the VAR model. Study findings showed a strong presence of overconfidence bias in the market (Chuang & Lee, 2006). Presence of overconfidence bias in the French stock market during the period from 1988 to 2004 was also studied with the help of VAR model and the study evidenced the presence of overconfidence bias in the stock market (Siwar, 2011). However, a study in Tunisian stock market with VAR model on monthly data during the period from January 2000 to December 2006 showed little evidence of overconfidence bias in the market (Salma & Ezzeddine, 2008). Overall, studies using the VAR model showed that overconfidence behaviour is less common (emphasised) in emerging markets when compared to developed markets (Griffin, Nardari & Stulz, 2007).

Overconfidence bias in sectoral indices of Indian stock market has been explored by using VAR model by comparing the level of influence of overconfidence bias during pre-COVID-19 phase and during COVID-19 phase. The result shows that all cyclical sectors exhibit more level of overconfidence bias than defensive sectors. However, during the COVID-19 phase overconfidence bias was more pronounced in IT and Pharma sectors along with metal, media, and realty sector. The study also found out that overconfidence bias has no influence in the energy sector (Azam, Hashmi, Hawaldar, Alam & Baig, 2022). Focusing on the determinants of overconfidence bias it was found that all the cognitive biases influence overconfidence bias and illusion of control is the most influencing variable (Ul Abdin, Qureshi, Iqbal & Sultana, 2022). The influence of overconfidence bias has been explored during the upswing and downswing phases and it was found that the investors who trade more frequently and in large volume are overconfident in the information they possess during the upswing phase, while during the downswing phase they are reluctant to trade and possess less confidence (Huang, Wang, Fan & Li, 2022). The influence of behavioural biases on the mindset of investors shows that company history information, location benefit and IPO issues play a significant role in influencing the investment strategies (Soni & Desai, 2021).

Previous studies, mostly in developed markets, have established a link between volume traded and lagged returns (Statman et al., 2006; Chuang & Lee, 2006; Glaser & Weber, 2007; Glaser & Weber, 2009). However, studies in emerging markets are fewer in number. A study in India has established the presence of many irrational biases in investors such as self-attribution bias, framing effect bias, overreaction bias, etc. (Singh, Goyal & Kumar, 2016). However, the present study considers Nifty 50 index as the market representative and the daily data for these market indices were taken over a period of ten years beginning 1st April 2005 to 31st March 2015. The objective of the study is to find out the presence of overconfidence bias by examining the relationship between market return, trading volume and price volatility. The study also aims to find out how long this overconfidence bias persists in the market.

Data and methodology

The present study is carried out entirely through secondary data made up of volume traded, closing price, high price, and low price of Nifty 50 index on daily basis during the period from 1st April 2005 to 31st March 2022 obtained from National Stock Exchange of India (NSE) website. As trading volume cannot be applied directly in the VAR model, log value of trading volume and market return were calculated.

Volatility is calculated by using the Parkinson model (1980) by taking high and low market values.

$$Volatility = \sqrt{250} * \sqrt{\frac{1}{4*\ln(2)} * \ln\left(\frac{h}{l}\right)^2} \tag{1}$$

Where:

h: high value during the day,

l: low value during the day.

To check the stationarity of the data considered for the study period Augmented Dickey-Fuller (ADF) test and Philip Perron (PP) test have been used before model application to investigate the presence of overconfidence bias. Vector autoregression (VAR) is a stochastic process model that generalises the single variable to multivariate time series autoregression. VAR on market wide transaction was applied to study the presence of overconfidence bias in the market and its validity period was verified with the help of impulse response function.

$$LogT_t = \propto + \sum_{j=1}^{k} \beta_j \, LogT_{t-j} + \sum_{j=1}^{k} \gamma_j \, Rm_{t-j} + vvol_t + \varepsilon_{1t} \tag{2}$$

$$Rm_t = \propto ' + \sum_{j=1}^{k} \beta'_j \, LogT_{t-j} + \sum_{j=1}^{k} \gamma'_j \, Rm_{t-j} + v' vol_t + \varepsilon_{2t} \tag{3}$$

Where:

LogT: is the log value of the trading volume of market index,
R_m: is the log value of daily market return,
Vol: is the value of daily volatility of market,
k: is the number of lags,
j: is the index of summation for the lags,
t: number of observations,
ε: error term.

Here, the dependent variables are log value of trading volume and daily market return of Nifty. The independent variables are daily volatility, lagged values of trading volume and lagged market return. The regression coefficients β and γ estimate the time series relationships between dependent variable and independent variables. The VAR methodology allows for a covariance structure to exist in the residual vector ε_t, that captures the contemporaneous correlation between dependent variables. The volatility control variable is based on a study of contemporaneous volume-volatility relationship (Karpoff, 1987) and is similar to the mean absolute deviation measure in the study of trading volume (Bessembinder, Chan & Seguin, 1996).

Formal overconfidence theories do not specify a time frame for the relationship between return and volume of trade. Therefore, the number of optimum lags is decided on the basis of the values of Schwarz Information Criterion (SIC).

The study assumes:

Hypothesis: H1: There is no presence of overconfidence bias in the market.

The VAR model was applied to find out whether the Indian stock market is under the influence of the overconfidence bias of the investors. VAR model application was used to study the relationship between log value of trading volume and market return as dependent variable and lag value of trading volume, lag value of market return and log value of volatility as independent variables.

Results and discussion

The stationarity of the variables have to be inspected before applying the variables in the model. Hence, the stationarity Augmented Dickey-Fuller (ADF) and Philip Perron tests have been applied to check the stationarity of log value of volume traded, market return and price volatility.

The results of Augmented Dickey-Fuller (ADF) test and Philip Perron (PP) test are tabulated in table 1.

The table explains the output of unit root test for the variables log value of volume, market return and volatility with the help of ADF and PP test. The result of both ADF and PP tests show that there is no unit root in any of the variables.

Table 1. The Result of Unit Root Test

Variable	ADF		PP	
	t-stats	P-Value	t-stats	P-Value
Log of Trading volume (T)	-3.787***	0.003	-27.239***	0.000
Log Value of Market return (Rm)	-62.584***	0.0001	-62.554***	0.000
Log Value of Volatility (Vol)	-3.264**	0.017	-16.089***	0.000

Note ***: 1% level of significance **: 5% level of significance.

Source: computed data.

From the results it is very clear that there is no unit root in any of the variables, as the calculated test statistics of ADF and PP are significant at 1% level for the log value of volume traded and market return whereas log value of volatility showed significance at 5% level. The VAR model can be applied to study the presence of overconfidence in the market. As formal overconfidence theories do not specify a time frame for the relationship between market return and volume of trade, the number of optimum lags is decided on the basis of lag determination test based on Schwarz Information Criterion (SIC) and the result of lag determination test is tabulated in table 2 in the Annexure.

Lag determination test is applied to find out the optimum number of lags in the VAR model. The result shows that based on SIC criterion number of lags are determined as six.

Table 2. Lag Determination Test

Lag	SIC	Lag	SIC	Lag	SIC
0	-4.208	10	-5.288	20	-5.239
1	-5.088	11	-5.282	21	-5.231
2	-5.206	12	-5.280	22	-5.224
3	-5.244	13	-5.273	23	-5.217
4	-5.273	14	-5.267	24	-5.211
5	-5.292	15	-5.264	25	-5.205
6	-5.294*	16	-5.257	26	-5.197
7	-5.294	17	-5.251	27	-5.189
8	-5.292	18	-5.245	28	-5.183
9	-5.289	19	-5.242	29	-5.176

Note *: 5% level of significance.

Source: computed data.

The * (sign) denotes the lag order selected by Schwartz Information Criterion (SIC) at 5% level of significance. Accordingly, the presence of overconfidence bias was found out using the VAR model with number of lags k = 6 in equation (3). The results are summarised in the table 3 and table 4. Table 3 represents the relationship between trading volume and lag of market return and between market return and lag of volume traded.

This table shows the output of VAR by explaining the relationship between trading volume (Dependent Variable) and lag of Market Return (Independent

Variable) and the relationship between market return (Dependent Variable) and lag of trading volume (Independent Variable). Higher R^2 and Adjusted R^2 value in the table shows the better model.

Table 3. Relationship between Trading Volume (T) and Market Return (R_m) lags using VAR

		$R_m(-1)$	$R_m(-2)$	$R_m(-3)$	$R_m(-4)$	$R_m(-5)$	Rm(-6)	R^2	Adj R^2
Trading Volume (T)	Coefficient	0.330	0.781	-0.174	0.164	0.466	0.377	0.812	0.811
	SE	0.321	0.321	0.320	0.320	0.320	0.320		
	t-statistic	1.028	2.437	-0.543	0.512	1.454	1.179		
	P-Value	0.304	0.014	0.587	0.608	0.146	0.238		
		T(-1)	T(-2)	T(-3)	T(-4)	T(-5)	T(-6)	R^2	Adj R^2
Market Return (R_m)	Coefficient	0.0010	0.0005	0.0002	-0.0003	-0.0001	0.001	0.012	0.009
	SE	0.0007	0.0008	0.0008	0.0008	0.0008	0.001		
	t-statistic	1.4210	0.0577	0.2151	-0.3607	-0.0838	0.760		
	P-Value	0.155	0.954	0.83	0.718	0.933	0.447		

Note: **: 1% level of significance.

Source: computed data.

Table 3 summarises the coefficient value, standard error, t-statistics, P-value, R^2 and adjusted R^2 in the relationship between trading volume & lag of market return and similarly market return & lag of trading volume. As R^2 value indicates the better model, the model with trading volume as endogenous variable is a better one for the study. The relationship between trading volume and lagged market return is used to indicate the presence of overconfidence in the market. A positive relationship between trading volume and lag of market return is taken as evidence of overconfidence bias in the market (Odean, 1998a; 1998b; 1999; Gervais & Odean, 2001; Barberis & Thaler, 2003; and Statman et al., 2006). Out of six lags, the third lag showed a negative coefficient value whereas 1st lag, 2nd lag, 4th lag and 5th lag showed positive values. In that second lag alone had a 5% significance. The reason for the second lag significance is the T+2 days settlements prevailing in the Indian market or the laggard activity among these investors. According to the theory, overconfidence bias is the most prominent explanation for the nature of this excess volume.

Table 4 given below represents the relationship between trading volume & price volatility and similarly market return & price volatility. Here, the trading volume and market return are endogenous variables and price volatility is an exogenous variable.

Table lists out the remaining output of VAR model which explains the relationship between trading volume (Dependent Variable) and Price Volatility (Independent Variable) and Market Return (Dependent Variable) and Price Volatility (independent Variable). The result shows that there is a significant positive relationship between volume and volatility and a negative relationship between market return and volatility at 1% level of significance.

Table 4. Relationship between Trading Volume, Market Return and Price Volatility using VAR

Variable		Price Volatility
Trading Volume	Coefficient	0.916
	SE	0.009
	t-statistics	10.041
	P-Value	0.000
Market Return	Coefficient	-0.002
	SE	0.001
	t-statistics	-5.052
	P-Value	0.000

Source: computed data.

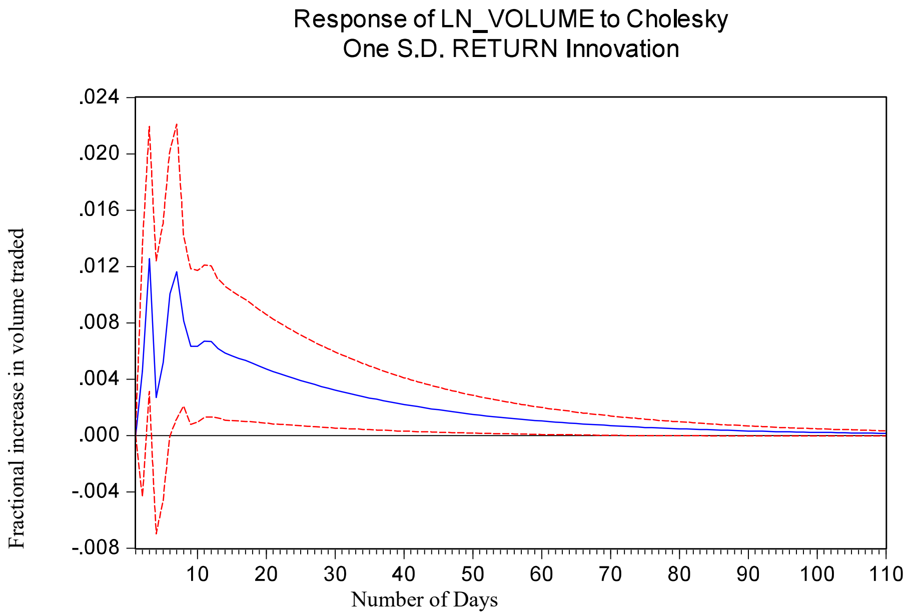
Table 4 exhibits a positive relationship between trading volume and price volatility and a negative relationship between market return and price volatility at 1% level of significance. This finding is consistent with the findings of Karpoff (1987) and Statman et al. (2006). The findings of the relationship between market return and trading volume in the present study produce enough evidence to prove that investors are trading more even when the market becomes highly volatile assuming it as a positive signal and ends up in low return, consistent with the overconfidence theory. They end up in low return because of the overconfidence on the information possessed by them leading to market speculation. Previous studies in Indian market have produced ample evidence of volatility signals in commodity and equity indices generating speculative trading in the market. These results thus confirm the presence of overconfidence bias among traders in Indian market. Hence, it is proved that the null hypothesis is rejected at 1% level of significance and the alternative hypothesis is accepted, i.e., H1: There is a presence of overconfidence bias in the market.

Market impulse response functions

Impulse response functions use all the VAR coefficient estimates to trace the impact of a residual shock that is one standard deviation from zero. Figure 1 in annexure explains the response of volume traded to market return with one standard deviation of change in return. The vertical axis in the figure indicates the fractional increase in volume traded and the horizontal time axis represented in days. The figure shows that there is a positive response of volume traded to change in market return, the effect ranges around 0 to 0.013 percent and reaches a peak value of more than 0.01% for one standard deviation shock to market return during the second and third day. After a slight decline again it reaches the level of 0.012% after the 6thday. The high volume of trading then started declining gradually from 7th day onwards and reached around 0.007% on 11th day and thereafter the market witnessed a steep decline but the bias persists for more than 110 days. Thus, the return to volume effect prevails in the market around four months.

The figure shows that there is a positive response of volume traded to change in return. This effect persists in the market for 110 days.

Figure 1. Response of Volume Traded to Market Return with One Standard Deviation of Change in Return

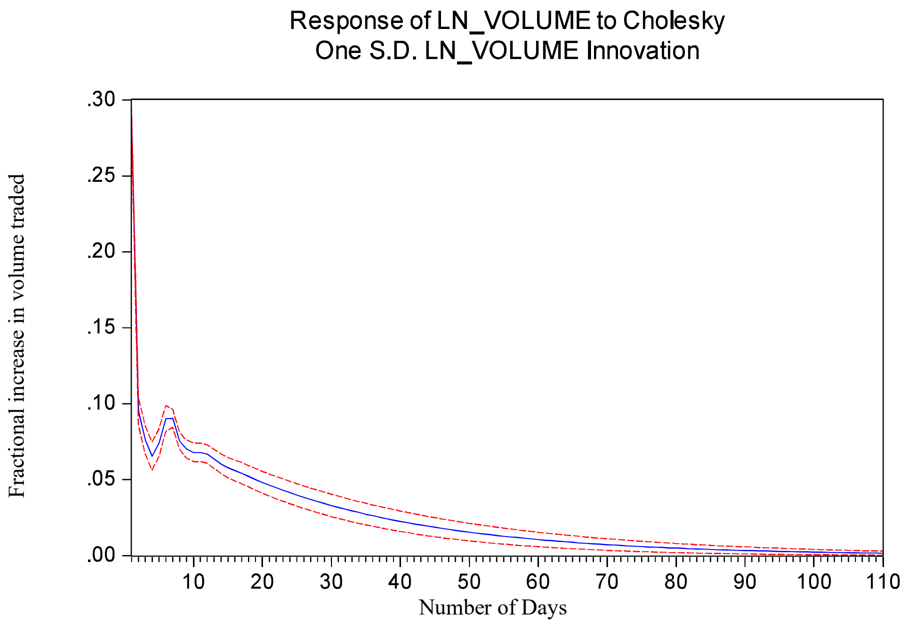


Source: computed data.

Figure 2 in the annexure explains the response of trading volume towards its own lag due to one standard deviation of change in lag value of volume traded. The vertical axis in the figure indicates the fractional increase in the trading volume while the horizontal axis gives the time in days. The figure shows that there is a positive response of trading volume to the lag value of volume traded, which ranges between 0 to 0.29 percent. The effect of its own first lag on the same day is around 0.29 percent and from the next day the effect has started declining steeply and dropped to around 0.095 percent on 2nd day. Later, it has decreased till the 4th day to 0.065% and started to increase again up to the 6th day to 0.09% thereafter started to decline steeply after 7th day but the lag effect persists even after 110 days. Thus, the results show that after brief fluctuations and high trading volume for seven days and the effect prevails in the market around four months.

The figure shows that there is a positive response of trading volume to the lag value of volume traded. The results show that after brief fluctuations the effect lasts for more than three months before attaining normal.

Figure 2. Response of Trading Volume Towards its Own Lag with One Standard Deviation of Change in Lag Value of Volume Traded



S o u r c e : computed data.

The results of figures 1 and 2 in the annexure give evidence of overconfidence bias among investors in Indian market. Figure 1 shows increased trading, consequent to an increase in market return, with the maximum increase of 2% consistent with the 2% to 4% increase in trading observed by Statman et al. (2006). Figure 2 shows that increased trading volume is also positively related to the previous days increase in trade, consistent with the overconfident investor behaviour. Both these results thus confirm the findings of Statman et al. (2006) and conventional market wisdom which indicate that a shock in market return and volume will enhance trading activity for at least a month or two.

This overconfidence bias may induce the investors to go for bulk or block trade on the stocks with which they perform better. These results are also in agreement with theories on overconfidence bias which says that increased trading can be exploited by investors to their advantage to make more than average returns for a sustained period of time, in apparent violation of an efficient market hypothesis.

Conclusion

Overconfidence bias is a psychological bias that may be defined as an excessive belief in one's intuitive reasoning, judgements and cognitive abilities (Pompian, 2008). The investors' lack of knowledge results in many of their decisions to be irrational and clouded by many behavioural biases including overconfidence bias.

Our study examines the presence of overconfidence bias in the stock market over a ten-year period using Vector Autoregression (VAR) model and we examine the persistence of this bias using impulse response functions. Our analysis found a positive relationship between trading volume and lag of market return as well as between trading volume and volatility, we further found the relationship between return and volatility to be negative. That is these investors trade actively (causing volatility) and lose (negative return) more often in the market. This market behaviour provides strong evidence for overconfidence bias existing among the traders in the Indian market and these effects persist for more than 110 days.

We found that the overconfidence in the Indian market is consistent with developed markets such as the US, and is unlike evidence of minimal overconfidence bias found in Asian and Latin American or developing markets (Griffin et al., 2007). This overconfidence bias could be a factor responsible for triggering and prolonging global financial countries in US and in countries across all continents (Jlassi, Naoui & Mansour, 2014). Hence, even though overconfident investors cause intense trading in the market, their frenzied activity even in volatile periods does not augur well for the prosperity of Indian investors and the market.

References

Azam, M.Q., Hashmi, N.I., Hawaldar, I.T., Alam, M.S., & Baig, M.A. (2022). The COVID-19 Pandemic and Overconfidence Bias: The Case of Cyclical and Defensive Sectors. *Risks*, 10(3), 56–70. http://dx.doi.org/10.3390/risks10030056.

Barber, B.M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics*, 116(1), 261–292. http://dx.doi.org/10.2139/ssrn.139415.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. *Handbook of the Economics of Finance*, 1(1), 1053–1128. http://dx.doi.org/10.3386/w9222.

Bessembinder, H., Chan, K., & Seguin, P.J. (1996). An empirical examination of information, differences of opinion, and trading activity. *Journal of Financial Economics*, 40(1), 105–134. http://dx.doi.org/10.1016/0304-405x(95)00839-7.

Bondt, W.F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3), 793–805. http://dx.doi.org/10.1111/j.1540-6261.1985.tb05004.x.

Bondt, W.F., & Thaler, R. (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance,* 42(3), 557–581. http://dx.doi.org/10.1111/j.1540-6261.1987.tb04569.x.

Chuang, W.I., & Lee, B.S. (2006). An empirical evaluation of the overconfidence hypothesis. *Journal of Banking* & *Finance*, 30(9), 2489–2515. http://dx.doi.org/10.1016/j.jbankfin.2005.08.007.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance*, 53(6), 1839–1885. http://dx.doi.org/10.1111/0022-1082.00077.

Dittrich, D.A., Güth, W., & Maciejovsky, B. (2005). Overconfidence in investment decisions: An experimental approach. *The European Journal of Finance*, 11(6), 471–491. http://dx.doi.org/10.1080/1351847042000255643.

Gervais, S., & Odean, T. (2001). Learning to be Overconfident. *The Review of Financial Studies*, 14(1), 1–27. http://dx.doi.org/10.1093/rfs/14.1.1.

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. *The Geneva Risk and Insurance Review*, 32(1), 1–36. http://dx.doi.org/10.1007/s10713-007-0003-3.

Glaser, M., & Weber, M. (2009). Which past returns affect trading volume? *Journal of Financial Markets*, 12(1), 1–31. http://dx.doi.org/10.1016/j.finmar.2008.03.001.

Griffin, J.M., Nardari, F., & Stulz, R.M. (2007). Do investors trade more when stocks have performed well? Evidence from 46 countries. *Review of Financial Studies*, 20(3), 905–951. http://dx.doi.org/10.1093/rfs/hhl019.

Huang, J., Wang, Y., Fan, Y., & Li, H. (2022). Gauging the effect of investor overconfidence on trading volume from the perspective of the relationship between lagged stock returns and current trading volume. *International Finance*, 25(1), 103–123. http://dx.doi.org/10.1111/infi.12405.

Jlassi, M., Naoui, K., & Mansour, W. (2014). Overconfidence Behavior and Dynamic Market Volatility: Evidence from International Data. *Procedia Economics and Finance*, 13(1), 128–142. http://dx.doi.org/10.1016/S2212-5671(14)00435-3.

Karpoff, J.M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis*, 22(01), 109–126. http://dx.doi.org/10.2307/2330874.

Kamesaka, A., Nofsinger, J. R., & Kawakita, H. (2003). Investment patterns and performance of investor groups in Japan. *Pacific-Basin Finance Journal*, 11(1), 1–22. http://dx.doi.org/10.1016/S0927-538X(02)00095-1.

Koutmos, D., & Song, W. (2014). Speculative Dynamics and Price Behaviour in the Shanghai Stock Exchange. *Research in International Business and Finance*, 31(1), 74–86. http://dx.doi.org/10.1016/j.ribaf.2013.11.006.

Lee, C., Shleifer, A., & Thaler, R.H. (1991). Investor sentiment and the closed-end fund puzzle. *The Journal of Finance*, 46(1), 75–109. http://dx.doi.org/10.1111/j.1540-6261.1991tb03746.x.

Odean, T. (1998a). Volume, volatility, price, and profit when all traders are above average. *The Journal of Finance*, 53(6), 1887–1934. http://dx.doi.org/10.1111/0022-1082.00078.

Odean, T. (1998b). Are investors reluctant to realize their losses? *The Journal of Finance*, 53(5), 1775–1798. http://dx.doi.org/10.1111/0022-1082.00072.

Odean, T. (1999). Do Investors Trade Too Much? *American Economic Review*, 89(5), 1279–1298. http://dx.doi.org/10.1257/aer.89.5.1279.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business*, 53(1), 61–65. http://dx.doi.org/10.1086/296071.

Pompian, M.M. (2008). *Behavioral finance and wealth management*. *How to Build Optimal Portfolios That Account for Investor Biases*. Hoboken, New Jersey: John Wiley & Sons Inc.

Salma, Z., & Ezzeddine, A. (2008). Overconfidence And trading volume: Evidence from an emergent market. *Annales Universitatis Apulensis Series Oeconomica*, 1(10), 378–387.

Singh, H.P., Goyal, N., & Kumar, S. (2016). Behavioural Biases in Investment Decisions: An exploration of the role of Gender. *Indian Journal of Finance*, 10(6), 51–62. http://dx.doi.org/10.17010/ijf/2016/v10i6/94879.

Siwar, E. (2011). The impact of overconfidence bias and disposition effect on the volume of transaction and the volatility of the French stock market. *Journal of Applied Economic Sciences*, 1(15), 61–83.

Soni, K., & Desai, M. (2021). Stock Prices: Effect of Behavioral Biases on Investor's mindset in Gujarat State, India. *Copernican Journal of Finance* & *Accounting*, 10(1), 67–79. http://dx.doi.org/10.12775/CJFA.2021.004.

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor Overconfidence and Trading Volume. *The Review of Financial Studies*, 19(4), 1531–1565. http://dx.doi.org/10.1093/rfs/hhj032.

Ul Abdin, S.Z., Qureshi, F., Iqbal, J., & Sultana, S. (2022). Overconfidence bias and investment performance: A mediating effect of risk propensity. *Borsa Istanbul Review*, 22(4), 780–793. http://dx.doi.org/10.1016/j.bir.2022.03.001.