



THE IMPACT OF BEHAVIORAL BIASES ON INVESTOR'S BEHAVIOR IN INDIAN STOCK MARKET

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Abstract

Capital Asset Pricing Model, Efficient Market Hypothesis and Modern Portfolio Theory (Traditional Financial Theories) presumes that financial markets are perfect and all the investors behave rationally. In other words, these theories believe that whatever new information comes in the market, it is instantly absorbed by the stock prices; thus, eliminating the possibility of earning more profits just by having the company's insider information. But, there are many empirical studies done before which shows that investors while trading in stock market are not rational always, rather their decisions are affected by many other factors. Thus, the present paper focuses on determining the various behavioral biases that influence investor's decision making process. The data for the same was gathered from 380 respondents residing in Delhi/NCR to test the presence of Loss Aversion, Regret Aversion, Herd Behavior, Overconfidence Bias and Cognitive Dissonance Bias. Further, Principal Component Analysis was used to analyse the collected data. It was found that all these biases have moderate impact on the investor's decision making process. These findings shall help the investors in understanding the most common behavioral biases to which they are vulnerable to in order to help them to mitigate the risk factor in investment for better returns. It shall also help financial planners in customizing portfolios and asset allocation strategies for their clients.

Keywords: Behavioral Finance, Herd behavior, Overconfidence bias, Regret Aversion, Cognitive Dissonance, Loss Aversion.

JEL Classification: G02, G110, G12, O16.

1. Introduction

There is a voluminous theory and affirmation in literature which shows that investors do not behave rationally always, specifically when it is related to risky investments. Moreover, share market in the past decade has done considerably well giving more than 15% returns. But when it comes to the performance of the investor's portfolio; majority of the investors come out with a view that share market is ambiguous, volatile and has cleaned off their money. Alike, experienced and experts as well were not able to outshine the market. Individual investor's behavior was taken into consideration in many researches and it was found that they do not take investment decisions rationally; rather their decisions are influenced by many psychological factors. This gives a new opportunity to the academicians and researchers to study investor's psychology in depth in order to find out the reasons why they do not behave rationally. This need to study human behavior gave birth to a new concept called Behavioral Finance.

Behavioral Finance put together the ideas of traditional finance theories and various psychological factors to examine how they affect investor's behavior leading to irrational decision making. Most of the time, investors get trapped in their own and sometimes in other's mistakes just only because of ignoring company's fundamentals and taking decisions emotionally. Thus, it becomes very important to examine the various types of behavioral biases to which investors' may get prone to and how each one of them affects their decision making process. And the present research paper takes into consideration all these issues.

1.2 The Specific Objectives of the Study are

- To examine various behavioral biases and how they affects investor's investment decision making process.
- To check if any behavioral bias exists among investors.

2. Review of Literature

Despite the fact that a lot of research has been done for studying investor's behavior in the past few decades but the concept of behavioral finance has become popular only after financial crisis 2008. Behavioral finance opines that stock markets are inefficient as investors do not take their decisions rationally; rather they involve their emotions in decision making process. Thus, it becomes essential to subsume human behavior traits with the concepts of traditional finance to get an idea on why they behave irrationally and ignores company's fundamentals and the latest available information in the market **Razek (2011)**. While, **Agrawal (2012)** has given an elaborated theoretical view of distinct psychological biases by demonstrating how they eventuate, their impact and how are they connected with each other. He found that it is not possible to study these biases in seclusion; as they are likely to emanate from other biases and tend to be present at the same time.



Moreover, it has also been observed that in spite of Efficient Market Hypothesis strong principles, stock markets come across with a number of abnormalities which results in superfluous volatility leading to irrationality in decision-making. These abnormalities are visible in the form of calendar effect, splitting of stocks, investment done after evaluation of performance, tax saving benefits and many more. **Muhammad (2009)** investigates the rationality in investors' decision making process. He found that majority of the investors limit their investment to specific asset categories and try to avoid losses by taking decisions emotionally. He also mentions that investors tend to follow their peer group and sometimes use past performance of the stock to forecast its future price. Moreover, it was also found that investors' prefer only those stocks for trading with which they are familiar. **Chandra (2011)** carried out his study to investigate the abnormalities in SENSEX for the period April 1998 to March 2008. He found that calendar effect was present in SENSEX as a result of which starting days of the month shows higher returns as compared to the remaining days of the same month. **Kaur (2011)** in her study confirms the presence of month-of-the year effect for the period January 2002 to December 2009 in BSE 500 and S&P CNX 500. She found that returns were higher in the month of December as compared to remaining months. **Kumar (2012)** chooses Diwali period for this study to check if trading volume increases during post mahurat period or not. Surprisingly, he found that trading volume was huge during the selected period which results in increase in volatility and stock returns.

Generally, it is observed that if a stock purchased by investors goes down, he will hold on to that stock in the hope that it will reach its high but when it comes to profitable stocks, they sell them too soon. Moreover, investors are likely to be more disappointed by holding loser stocks than with selling winner stocks too soon. **Fogel and Berry (2006)** found in their study that investors do not get upset on negative returns if they arise due to brokers or advisors advices, across both buying and selling. **Barberis and Huang (2001)** examined and found that a loss after having a profit hurt less; on the other hand, a loss after a loss emerges to be more painful. Sometimes, investors find it difficult to take decision due to the uneasiness that it will end in poor outcome. Such a behavior is called as regret aversion bias. **Siddiqui (2008)** examines the effect of disposition bias and found that investor's first concern was the safety of their investment amount. Moreover, they give credit to their own analysis if it results in profits whereas blame others for the losses. **He and Shen (2010)** examines whether investors use past performance of the stocks to forecast the future return and found positive association between predicted returns and future returns for portfolios based on market and individual stocks.

On the other hand, **Hirshleifer et.al (1998)** in their study found that overconfident investors have a propensity to give more preference to their knowledge and experience as compared to the publicly available information. Investors' are likely to be more overconfident if their own information conforms with the public information; but in case of contradiction, it does not bring any change in their confidence level.

Qian (2009) examines the changes in analysts' confidence due to changes in investor's emotions after controlling GDP and institute that analysts are immensely positive for small companies as in relation to large companies. Author also found that growth in economy results in trimming down the analyst confidence. **Barber and Odean (2000)** carried out their study to analyse the households' investment and found that investors' prefers to trade only in those stock with they are familiar and are likely to avoid unfamiliar stocks. **Barber and Odean (2001)** carried out their study to check if overconfidence results in enormous trading and lower returns. They found that there is a huge difference in trading strategies of single men and women. They also found that investors are likely to be more confident and optimistic when they trade in interactive environment due to which they trade excessively and their performance falls. On the other hand, investors who trade in closed environment are likely to trade cautiously resulting in higher returns **Cheng (2007)**.

3. Data and Research Methodology

Primary data has been collected for the present research paper with the help of a questionnaire distributed to respondents residing in Delhi/NCR region. The data of the respondents was collected from reputed brokerage houses. Investors were selected randomly using random number generator to assure that the selected sample size correctly represent the population. Then, questionnaires were distributed to respondents during October 2015 to April 2016. The questionnaire contains 2 parts- first contains personal information of the respondents and second part contains questions related to psychological biases. Only 419 questionnaires were received out of which only 380 were selected for analysis.

The present paper used the methodology used by Vijaya E.(2014). Factor Analysis (Principal Component Analysis) and Cronbach's Alpha test were used on SPSS 21.0 for analysing the data. The Principal Component Analysis advocates that the number of components extracted is equal to the number of variables analysed. In this, only the first few extracted components are important in explaining variance and the subsequent components are useful in explaining only inconsequential variance. Further, the reliability of various factors is measured by Cronbach's Alpha, most commonly used coefficient of reliability.



4. Empirical Analysis

Part-A

4.1A. Bartlett test of Sphericity and Kaiser-Meyer-Olking Measure of Sampling Adequacy

The questions are intended to investigate the impact level of behavioral biases on investor's decisions. The Principal Component analysis is used for analysing these factors and to find which variables are related to which factors. After eradicating the inappropriate variables, the remaining variables are grouped in 3 factors.

First of all, Bartlett test of Sphericity and Kaiser-Meyer-Olking Measure of Sampling Adequacy is carried out. Bartlett test of Sphericity is used to test the null hypothesis that the correlation matrix is an identity matrix and this null hypothesis has to be rejected. Further, the value of Kaiser-Meyer-Olkin Measure of Sampling Adequacy ranges from 0 to 1 where a value near to 1 is considered better but less than 0.5 is considered inadequate. Any variable having MSA below 0.5 has to be removed from the analysis. It can be seen from **table 2**(after removing A3 variable)that the MSA for one variable (A3) was less than 0.5, thus it was removed from the analysis. Whereas overall MSA (table 1) is 0.724 and MSA for all the variables are above 0.5 which is a good indicator. Moreover, Bartlett's Test of Sphericity has a p value which is 0.000 (table 1) which further validates that factor analysis can be carried forward.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.724
Bartlett's Test of Sphericity	Approx. Chi-Square	371.575
	df	45
	Sig.	.000

Source: Primary survey

		A1	A2	A4	A5	A6	A7	A8	A9	A10	A11
Anti-image Covariance	A1	.898	-.099	-.060	-.096	.161	-.089	.034	-.059	-.037	-.086
	A2	-.099	.863	-.064	-.015	-.022	.014	-.149	-.032	-.009	-.158
	A4	-.060	-.064	.848	-.095	-.109	-.041	-.039	-.087	-.003	-.108
	A5	-.096	-.015	-.095	.805	-.115	-.051	-.222	-.067	.009	.006
	A6	.161	-.022	-.109	-.115	.805	-.166	.114	-.117	-.102	-.085
	A7	-.089	.014	-.041	-.051	-.166	.856	-.056	-.028	-.017	-.134
	A8	.034	-.149	-.039	-.222	.114	-.056	.795	-.155	-.057	.019
	A9	-.059	-.032	-.087	-.067	-.117	-.028	-.155	.825	-.107	-.024
	A10	-.037	-.009	-.003	.009	-.102	-.017	-.057	-.107	.919	-.088
	A11	-.086	-.158	-.108	.006	-.085	-.134	.019	-.024	-.088	.828
	Anti-image Correlation	A1	.609 ^a	-.113	-.069	-.113	.190	-.101	.040	-.068	-.041
A2		-.113	.747 ^a	-.075	-.018	-.026	.016	-.179	-.038	-.010	-.187
A4		-.069	-.075	.818 ^a	-.116	-.132	-.048	-.048	-.104	-.003	-.129
A5		-.113	-.018	-.116	.731 ^a	-.143	-.061	-.277	-.082	.010	.007
A6		.190	-.026	-.132	-.143	.618 ^a	-.200	.142	-.144	-.119	-.105
A7		-.101	.016	-.048	-.061	-.200	.762 ^a	-.068	-.033	-.019	-.159
A8		.040	-.179	-.048	-.277	.142	-.068	.642 ^a	-.192	-.067	.023
A9		-.068	-.038	-.104	-.082	-.144	-.033	-.192	.788 ^a	-.122	-.029
A10		-.041	-.010	-.003	.010	-.119	-.019	-.067	-.122	.782 ^a	-.100
A11		-.100	-.187	-.129	.007	-.105	-.159	.023	-.029	-.100	.751 ^a

a. Measures of Sampling Adequacy(MSA)

4.2A. Component Matrix: The component matrix is generated when the process of factor extraction starts. It shows unrotated factor loadings, depicting how a particular observed variable and a particular factor is related to each other. Higher correlation value indicates that both the variables are closely related to each other. They are explained in alike way as beta coefficients are explained in multiple regression analysis. Moreover any of the correlations value less than 0.3 are considered irrelevant and should be removed from the table. It can be seen from table 3 that principal component analysis has extracted 3 factors and all the values which are lower than 0.3 are removed.



Table 3: Component Matrix^a

	Component		
	1	2	3
A1	.335	.438	.540
A2	.485	.312	
A4	.561		
A5	.566		-.364
A6	.463	-.657	
A7	.509	-.301	
A8	.503	.493	-.415
A9	.580		-.307
A10	.398		
A11	.540		.497

Extraction Method: Principal Component Analysis.
 a. 3 components extracted.

4.3A. Communalities: The table 4 shows that the communalities, which shows the influence of all the factors associated with the particular observed variable. It is equivalent to the sum of squared factor loadings associated with observed variables and gives the same value as R^2 in multiple regression. Its value lies between 0 and 1, where 1 shows that the variable is totally explained by the factors and 0 shows that variable cannot be projected from any of the factors. Further, the value in extraction column signifies the part of each variable's variance that can be elucidated by the other factors. For example, variable that is explained most by the factors is A6 (0.677) followed by A8 (0.668), A1 (0.596) and so on.

Table 4: Communalities

	Initial	Extraction
A1	1.000	.596
A2	1.000	.409
A4	1.000	.323
A5	1.000	.504
A6	1.000	.677
A7	1.000	.375
A8	1.000	.668
A9	1.000	.432
A10	1.000	.209
A11	1.000	.577

Extraction Method: Principal Component Analysis.

4.4A. Total Variance Explained: Total variance explained signifies how much of the variability is explained by the extracted factors. The first column of the table shows components which are same as the number of variables used initially. However, after analysis only first three factors are kept having eigenvalues more than 1. Second column of the table shows initial Eigenvalues. Factors having eigenvalues more than one are only considered for the analysis. This column contains eigenvalues-where first factor always reports large variance and with each subsequent factor it goes on decreasing. Further, this column also shows the percentage of variance explained by each factor. Another column is rotated sums of squared loadings which shows the division of the variance after varimax rotation (which attempts to maximize the variance of each factor). However, in the below table (table 5), three factors are extracted and cumulatively they are accounted for 47.707% of the variance.

Table 5: Total Variance Explained

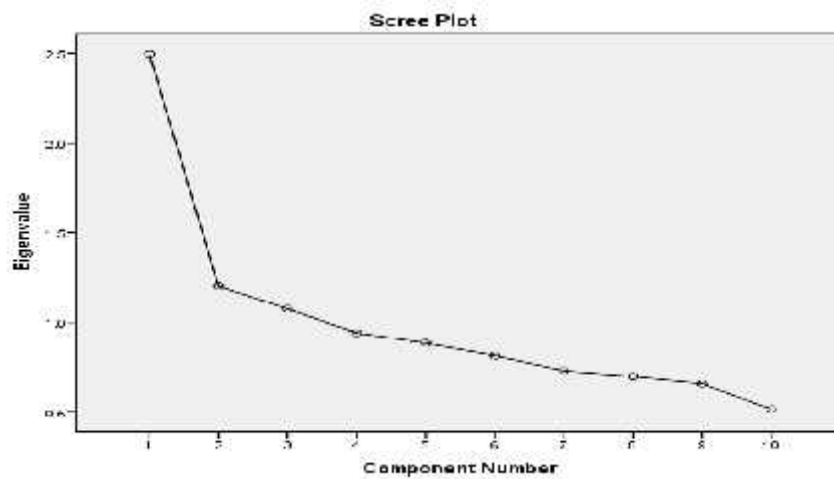
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.496	24.958	24.958	2.496	24.958	24.958	1.790	17.904	17.904



2	1.201	12.009	36.966	1.201	12.009	36.966	1.612	16.121	34.026
3	1.074	10.740	47.707	1.074	10.740	47.707	1.368	13.681	47.707
4	.939	9.388	57.095						
5	.883	8.830	65.925						
6	.813	8.132	74.056						
7	.728	7.283	81.339						
8	.696	6.962	88.300						
9	.655	6.547	94.848						
10	.515	5.152	100.000						

Extraction Method: Principal Component Analysis.

4.5A. Scree Plot: The scree plot is generated in the factor rotation phase. The scree plot displays the eigen value against respective factors. As it can be seen from the below diagram, in the first two plots the eigenvalues are relatively high and go on decreasing from third factor onwards. It shows that each subsequent factor after second variable accounts for less amount of total variance.



4.6A. Rotated Component Matrix: The rotated component matrix (table 6) shows the rotated component matrix which displays the rotated factor loadings. It shows the weightage of a variable in different factors and also the correlation between factor and the variables. Their value ranges from -1 to +1. However, any values below 0.3 are inadequate and are removed while comprehending which variable lies under which factor. Moreover, the column component shows the rotated factors that have been extricated. The SPSS has extracted three factors and these are the factors that an analyst is highly concerned about and attempts to name them.

	Component		
	1	2	3
A1			.769
A2			.572
A4	.439		
A5		.682	
A6	.777		
A7	.579		
A8		.802	
A9	.338	.563	
A10	.426		
A11	.555		.510

Extraction Method: Principal Component Analysis.
 Rotation Method: Varimax with Kaiser Normalization.
 a. Rotation converged in 5 iterations.



4.7A. Component Transformation Matrix: The component transformation Matrix (Table 7) is used to get the values of component rotated matrix by multiplying the unrotated component matrix with transformation matrix.

Component	1	2	3
1	.675	.599	.430
2	-.731	.469	.495
3	.095	-.649	.755

Extraction Method: Principal Component Analysis.
 Rotation Method: Varimax with Kaiser Normalization.

Part- B

Factor Loadings of Behavioral Biases

Table 8 shows that there are five behavioral biases that affect the decision making process of investors in Indian stock exchange. Further, in order to decide which variable will lie in which factor depends on the highest value of that variable in rotated component matrix. For example, A9 variable has two values in table 6, but it will be clubbed in F2 as it has the highest value in it. It can be seen in the table that all the variables of herding behavior and Cognitive Dissonance bias are grouped in one factor F1. whereas all the variables of Loss aversion bias in F3, overconfidence bias in F2 and Regret aversion belongs to two factors- F1 and F2. In Regret Aversion (A4 & A5), Herd Behavior (A6 & A7), Overconfidence Bias (A8 & A9) and Cognitive Dissonance bias (A10 & A11) all the variables are kept in the analysis; whereas only two variables (A1 and A2) in Loss Aversion Bias are kept as A3 was removed after analysis.

Table 8: Factor Loadings of Behavioral Biases

Factors	Questions	Factor Loading		
		F1	F2	F3
Loss Aversion	A1: You feel happy when your investments start making profit.			0.769
	A2: You feel very low after incurring losses on your investments.			0.572
Regret Aversion	A4: You avoid selling shares if their value comes down.	0.439		
	A5: You regret when you are not able to buy/sell a share when opportunity strikes.		0.682	
Herd Behavior	A6: When you don't have information of a stock, you usually follow what majority of investors are doing.	0.777		
	A7: Your attitude towards a stock will change if all your colleagues starts buying/selling that stock.	0.579		
Overconfidence Bias	A8: You are confident that your skills and knowledge can help you to outperform the market		0.802	
	A9: You are generally sure about your decisions because you made more profits than losses.		0.563	
Cognitive Dissonance bias	A10: You buy/sell a stock after considering its past performance.	0.426		
	A11: You think that future trend of a share can be predicted on the basis of their past price movements.	0.555		

The reliability of various factors is measured by Cronbach's alpha, most commonly used coefficient of reliability. The Cronbach's alpha is calculated to measure the reliability of measurements and to ensure that they can be used for further analysis. Generally, a reliability coefficient of 0.5 or higher is considered acceptable. Table 9 shows that all the values of Cronbach's alpha are greater than 0.6 and all the values of corrected item-total correlation are more than 0.3. Moreover, the value of Cronbach's Alpha if any item is deleted is less than the respective factors values, and the significant F test value is less than 0.05, ensures that data is acceptable and reliable in nature.

Table 9: Cronbach's Alpha test for various items of factors

Factors	Variables	Cronbach's Alpha	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	F (sig.)
Loss Aversion	Q1	0.66	.39	.658	0.000
	Q2		.316	.636	
Regret Aversion	Q4	0.656	.374	.654	0.016



	Q5		.377	.623	
Herd Behavior	Q6	0.675	.47	.643	0.049
	Q7		.337	.631	
	Q8		.65	.636	
Overconfidence Bias	Q9	0.647	.592	.620	0.016
	Q12		.72	.648	
Cognitive Dissonance biasBias	Q13	0.693	.669	.625	0.05

Impact of Behavioral Biases on Individual Investors Decision Making

In the present study five point Likert scale is used and in order to estimate the influence of behavioral biases, the average values of these variables are taken to determine their impact level on individual investors' decision making with the below mentioned rules:

- Variables are said to have low impact if its average values lies between 2 and 3.
- Variables are said to have moderate impact if its average values lies between 3 and 4.
- Variables are said to have high impact if its average values are more than 4.

4.1A. Impact of Loss Aversion Bias

Factor	Variables	Mean	Std. Deviation
Loss Aversion Bias	A1: You feel happy when your investments start making profit.	3.497	1.0414
	A2: You feel very low after incurring losses on your investments.	3.218	1.0638

The result in the above table shows that both the variables of loss aversion bias (A1 and A2) have moderate impact (A1 mean = 3.497 and A2 mean = 3.218) on individual investor's decision making. This result is in confirmation with the previous studies which suggest a loss incurred by an investor is more painful as compared to the gain of equal amount. Moreover, after having gain investors tend to become more risk seeking whereas after having a loss they tend to become more risk averse.

4.1B. Impact of Regret Aversion Bias

Factor	Variables	Mean	Std. Deviation
Regret Aversion Bias	A4: You avoid selling shares if their value comes down.	3.250	1.0366
	A5: You regret when you are not able to buy/sell a share when opportunity strikes.	3.266	1.0146

The result in the above table shows that both the variables of regret aversion bias (A4 and A5) tend to have moderate impact (A4 mean = 3.250 and A5 mean= 3.266) on investor's decision making process. This show in order to avoid the regret of having losses investors tend to hold losing stock for long and sell off winning stocks too early.

4.1C. Impact of Herding Behavior Bias

Factor	Variables	Mean	Std. Deviation
Herding Behavior	A6: When you don't have information of a stock, you usually follow what majority of investors are doing.	3.132	1.0914
	A7: Your attitude towards a stock will change if all your colleagues starts buying/selling that stock.	3.124	1.01592

The results of the above table show that both the variables of Herd behavior have moderate impact on investor's decision making. It shows that when investors don't have much information of a stock, they usually follow what majority of investors do (A6 mean= 3.132). Even, despite of having sufficient information of a stock, if their colleagues starts buying/selling that stock it will lead to change in their attitude also (A7 mean= 3.124).

4.1D. Impact of Overconfidence Bias

Factor	Variables	Mean	Std. Deviation
Overconfidence Bias	A8: You are confident that your skills and knowledge can help you to outperform the market.	3.324	1.0002
	A9: You are generally sure about your decisions because you made more profits than losses.	3.279	1.0202



Results of the table show that both the variables of overconfidence bias have moderate impact on investor's decision making. It shows that investors are confident about their skills and knowledge that can help them to outperform the market (A8 mean= 3.324) and they are generally sure about their decisions as they made more profits than losses (A9 mean= 3.279). For example, during subprime mortgage crisis, stock prices of majority of the companies increased even though some of them were not even profitable. And suddenly after the crash, all those profit making shares without having strong fundamentals wiped away all the profits of the investors.

4.1E. Impact of Cognitive Dissonance Bias

Factor	Variables	Mean	Std. Deviation
Cognitive Dissonance Bias	A10: You buy/sell a stock after considering its past performance.	3.105	1.0115
	A11: You think that future trend of a share can be predicted on the basis of their past price movements.	3.105	1.0549

As it can be seen in the above table that both the variables of Cognitive Dissonance bias have average impact on investor's decision making. The investors buy/sell a share only after examining its prior performance (A10 mean= 3.105) and are of the view that prospective trend can be predicted on the basis of their prior price movements (A11 mean= 3.105). Investors who are more prone to Cognitive Dissonance bias unduly interpret decision rules and generally forego the news that controvert with their information. Moreover, it is one of the heuristics biases in which investors take decisions quickly on the basis of past records as it is easy to recall events in a small time span without any instantaneous analysis.

5. Conclusion

The results of Principal Component Analysis show that there are five behavioral biases namely, Loss Aversion, Regret Aversion, Herd Behavior, Overconfidence Bias and Cognitive Dissonance bias that affect the individual investor's decision making process in Indian Stock market. Moreover the variable of all the factors has moderate impact on investor's decisions except loss aversion which tends to have slightly more impact followed by overconfidence bias. The results of the study shows that following herd or being confident of skills and knowledge is appropriate to a certain limit but beyond that it may lead to bad investment decisions. It is recommended to the investors that they should cautiously analyse an investment before investing their money, but should not overly concern about the probable loss for future investment. Furthermore, this study is an examination of individual investors' behavior and not of institutional investors. This research paper has picked a very small sample of investors' randomly who are trading in Indian share market. Thus, it is essential to have extended research to validate the results of this research using larger sample size with more multiplicity of investors. As it is evident from the past few market movements that institutional investors plays a major role in uplifting the economy; thus, it becomes even more important to study behavioral aspects of institutional investors also.

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