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Assessing the Linkage of Behavioural Traits and Investment Decisions using SEM Approach

P. LAKSHMI[a]*, S. VISALAKSHMI[b], N. THAMARAISELVAN[c] AND B. SENTHILARASU[d]

[a,b,c,d]*Department of Management Studies, National Institute of Technology, Trichy 620015*

ABSTRACT

The goal of this research is to investigate to what extent long term and short term stock investors share different behavioural characteristics. A structural model is employed to compare the traits of the investors and examine how investment decision making and behavioural biases are related, as well compare the relative differences of behavioural biases such as Herding, Social Contagion, Representative Heuristic, Over Confidence, Risk Aversion, Disposition Effect and Cognitive Dissonance. Identification of behavioural traits commonly associated with investment tenure aids in providing opinions and framing trading strategies. The psychological impact of investment decision making among investors is studied through a sampling survey of 318 valid respondents from voluntary retail investors in India between Jan 2012 and May 2012. Based on structure equation modelling [SEM], path analysis is performed on how investment decision making and the proposed behavioural biases are related. Analytical results indicate that the structural path model closely fits to the sample data, implying the role of behavioural biases in investment decision making among individuals. Our results further demonstrate that long term and short term investors significantly differ in behavioural traits.

Key words: Long term and short term investment decisions, Behavioural finance, Herding, Social Contagion, Representative Heuristic, Over Confidence, Risk Aversion, Disposition Effect and Cognitive Dissonance.

INTRODUCTION

Retail investors are increasingly being regarded as vital to enhance liquidity and depth in the financial markets. Relative to institutional and professional investors

* Corresponding Author: E-mail: vlr_laxmi@yahoo.in
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these investors can easily and quickly participate or withdraw from the markets based on the prevailing market conditions. The primary aim of this paper is to analyse the relationship between investment decision making of long term and short term Indian retail investors and behavioural traits such as Herding, Social Contagion, Representative Heuristic, Over Confidence, Risk Aversion, Disposition Effect and Cognitive Dissonance.

Research on behaviour of individual investors of various countries has shown that their trading decisions are often biased. Maditinos, D. I., Ševic, Ž., & Theriou, N. G. (2007) found that Greek investors rely heavily on fundamental and technical analysis, and less on portfolio analysis. Fundamental analysis is being seen as the most important approach in the long-term, but technical analysis being the key factor in the short-term. Menkhoff *, L., & Schmidt, U. (2005) identified three popular trading strategies in fund management, i.e. buy-&-hold, momentum and contrarian trading are of significance for fund managers.

Existing studies have analysed the importance of analysts' outlook in investment decision making. But no prior attempt has been made to employ the behavioural traits commonly associated with investment tenure, in providing opinions and framing trading strategies.

Our research has both practical and academic importance. From the perspective of financial services institutions, by identifying the key characteristics of investors' behaviour relative to their investment horizon, it is promising to develop customized products and services. Another, latent apprehension is that increasing learning with regards to fund managers' skill in managing funds increases the salience of financial institutions. From a market performance perspective, pulling out from stocks after losses are a crucial part of the mechanism underlying the corrections associated with mispricing.

From an academic perspective, it provides an opportunity to test hypotheses concerning the behavioural aspects that influence the investment decisions of long term and short term individual investors. As the investment horizon becomes long, fluctuations out of frequent withdrawals will get reduced considerably and subsequently market volatility tends to soften. Also investors can reap extra returns when they hold their investments for longer periods. Therefore to provide significant perspectives on the influence of behavioural factors that are largely unobservable and remain latent in investment decision making, we employ structural equation modelling for the analysis. This approach advances previous research which paid much attention on bi-variate correlation. For this purpose, we develop scales having relevance to tenure of investments and various behavioural aspects, as well as measures of demographic profile, disposable income and investment experience. These items are included in a set of five constructs.

REVIEW OF LITERATURE

The review of literature is centred on the theoretical and empirical studies on the behavioural traits that are considered for the present study. The hypothesis for each behavioural aspect is framed based on the gaps that were found in existing literature and is also grounded on the issues that were missed out or those that remain unexplored in the Indian market context.

Herding, Social Contagion & Representative heuristic

Herding as per academic literature refers to the lemming-like behaviour of investors looking around, seeing what each other is doing, and heading in that direction. It represents the tendency of individuals to mimic the actions [rational or irrational] of a larger group. Contagion theory looks at the social event and conditions that make crowd behaviour possible. Once infected with the contagious thoughts, behaviour becomes irrational or illogical and people do things they normally would not. Any individual in the crowd who already has the idea becomes the carrier. Under the right circumstances, other members of the crowd become infected.

Hwang, S., & Salmon, M. (2004) exhibited that Herding in the US market had significant movements and persistence in both bullish and bearish markets. Caparrelli,F, D'Arcangelis, A. M & Cassuto, A. (2004) established that in Italy, Herding is present during extreme market conditions, both in terms of sustained growth rate and high stock levels.

Thomas C. Chiang *et al*., (2012) investigated the herding behaviour in Pacific Basin financial markets and found that herding is positively associated with stock returns and negatively linked to market volatility. Moatemri Ouarda *et al*., (2013) analysed the effects of herding behaviour in terms of returns, volatility and volume of transaction and revealed existence of herding in both bullish and bearish phases, increased herding tendencies associated with higher trading volume and greater volatility mainly due to increased activity of short term speculative traders. Bell AV (2013) found that market participants imitate the outlook of prominent individuals, along with an inconsistent share of the trading volume and because of this prices inflate leading to a potential market collapse. Stephanie Kremer Freie, Dieter Nautz (2012) showed that institutions exhibit herding behaviour on a daily basis. Also it was found that return setbacks on stock prices pointed to destabilizing impact of herds in the short term.

Representativeness is "the degree to which an event is similar in essential characteristics to its parent population and reflects the salient features of the process by which it is generated" Kahneman&Tversky[1984, 1992]. Representative Heuristic is a cognitive bias in which an individual categorizes a situation based on a pattern of previous experiences or beliefs about the scenario. There are several types of representative heuristics including the Gambler's Fallacy, Base Rate Fallacy and Conjunction Fallacy. Ali, A. [2011] affirmed that Australian investors were users having specific informational needs including the need to adequately evaluate companies' risks and returns

Guo Ying Luo (2012) established that in a competitive securities market, representativeness heuristic traders can emanate additional anticipated profit from the misevaluations than rational traders. Applying theory and computer simulations to the experimental data generated by humans, Roszczynska-Kurasinska, M. *et al*. (2012) hypothesized that when a majority of short term investors experience decoupling, they become locked in their positions, and their decision heuristics are immune to disconfirming information. This implied that under certain situations, the investors' anticipations incline to grow biased and once they are biased – they become predictable. This behavioural aspect could be valuable from a financial institutions' perspective. Based on this the hypotheses tested on herding behaviour, representative heuristic & social contagion for short-term and long-term investors is as follows:

> *H_1: 'Herding, Social Contagion & Representative heuristic' is related to both Long term and Short term investors.*

Over Confidence

People are poorly calibrated in estimating probabilities and usually overestimate their precision of the knowledge and ability to do well and about good things happening in future than bad. This theory summarizes how people form beliefs under uncertainty. The overconfidence effect is a well-established bias in which someone's subjective confidence in their judgments is reliably greater than their objective accuracy, especially when confidence is relatively high. Psychologists have determined that overconfidence causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. According to Bailey, W., & Kumar, A. [2010], behavioural factors influence the decisions of US individual investors to hold individual stocks as opposed to mutual funds, including passive index funds. Graham, J.R., Harvey, C.R., & Huang, H. [2009] had found that male investors, and investors with larger portfolios or more education, are more likely to perceive themselves as competent than investors who are female, have smaller portfolios, or have less education.

Abreu M & Mendes V (2011) investigated the strength of the positive association between frequency of trading and investors' self-confidence and their findings confirmed that overconfident investors traded more frequently. Thus we hypothesise that over confidence will have an effect on long term investors and short term investors.

> *H_2: 'Over confidence' is related to both Long term and Short term investors*

Risk Aversion, Disposition Effect & Cognitive dissonance

As per Regret Theory, people anticipate regret if they make a wrong choice, and take this anticipation into consideration when making decisions. This probably makes them loss-averse. Hirshleifer, D, & Ying, G [2001]. When thinking ahead, they may experience anticipatory regret, as they realize that they may regret in the future. This can be a powerful dissuader or create a specific motivation to do one thing in order to avoid something else.

Riedl, A., & Smeets, P. (2012) found that a large majority of the individual investors behaved non-strategically and are pro-social. But on the other hand strategic, socially responsible investors (with a long term investment horizon) are significantly less pro-social in the unidentified trust inclined activity. Huang, W. H., & Zeelenberg, M. (2012) revealed that when the return on investments exceeded prior expectations, the effect of foregone investment on regret disappeared in speculative retail traders.

Shefrin and Statman [1985] postulate that investors dislike to bear the pain of regret associated with a loss. Hence, they tend to defer realizing their losses while booking their profits regularly and term this the Disposition Effect. This theory argues that investors are predisposed to holding losers too long and selling winners too early. The findings of Barber, B. M., Lee, Y.-T., Liu, Y.-J., & Odean, T [2007] identified that in aggregate and individually, Taiwanese investors have a disposition effect; that is, investors prefer to sell winners and hold losers. The disposition effect exists for both long and short positions, for both men and women and tends to decline following periods of market appreciation. Another study on Taiwanese investors by Lin, H.-wen [2011] revealed that behavioural biases and demographic variables positively influence all the stages of rational decision making.

Kaustia, M. [2010] found that the empirical propensity of Finnish investors to sell a stock is increasing or approximately constant as the gain increases, whereas a reasonable parameterization of a prospect theory value function predicts that the propensity to sell will decline as the gain increases. Da Costa, N. *et al*. (2013) examined whether investing experience dampened the disposition effect, in a simulated experiment with the experienced and inexperienced investors and found that the more experienced investors are less affected.

According to Olsen, R.[2008], Cognitive dissonance is a discomfort caused by holding conflicting ideas and beliefs simultaneously. In a state of dissonance, people may feel surprise, dread, guilt, anger, or embarrassment. People respond differently to equivalent situations depending on whether it is presented in the context of a loss or a gain. [For example, after a prior gain, investors may be more risk seeking than usual, whereas after a prior loss, they tend to become more risk averse]. The theory of cognitive dissonance in social psychology proposes that people have a motivational drive to reduce dissonance by altering existing cognitions, adding new ones to create a consistent belief system, or alternatively by reducing the importance of any one of the dissonant elements.

Chang, T., *et al*. (2012) experimentally demonstrated that cognitive dissonance increased if the disposition effect in stocks was stronger. Antoniou, C., *et al*. (2013) considered whether news that contradicted investors' sentiment caused cognitive dissonance through an analysis of net order flows from small and large trades and indicated that small investors were slow to sell losers during optimistic periods. Adding to the previous propositions we hypothesize:

> *H_3: 'Risk Aversion, Disposition effect & Cognitive dissonance' is related to both Long term and Short term investors*

METHODOLOGY

Data Collection, Questionnaire Development and Sample

Our primary data set for this research was information from two sources; initially through circulation of questionnaire to 125 clients of brokerage firms on their investment behaviour. Additionally, an online survey was conducted at the national level. The online survey was open between Jan 2012 and May 2012. Financial professionals and investors interested in participating in the study were asked to click on a survey link. The link connected the respondents to the survey, which contained questions on general demographics investment tenure, investment behaviour and experience. 193 responses were received through the online survey. The investment and behavioural traits are assessed by 5-point Likert scales with end points labelled "strongly agree" and "strongly disagree", "very important" to "irrelevant" and "always" to "never." Therefore data from a total of 318 samples were included in construction of the structural equation model[SEM]. Our structural model consists of 5 constructs: **i)** Long term Investors ii) Short term Speculative Investors iii) Herding, Social Contagion & Representative Heuristic iv) Over Confidence v) Risk Aversion, Disposition Effect & Cognitive Dissonance

The Structural Equation Model

The study uses structural equation model [SEM] to simultaneously estimate and explore how the investment decision-making process of long term and short term investors and the behavioural biases are related. The hypothetical model is proposed and analyzed with the LISREL 8.70 statistics package. The structural equation of the Model is:

$$\eta_i = \beta_{ij}\eta_j + \gamma_{ij}\xi_j + \varsigma_i \qquad i,j = 1, 2, 3... \qquad [1]$$

where ξj denotes exogenous latent variables, that is long term and short term investors; ηi denotes endogenous latent variables, that is risk aversion, herding, and overconfidence; γij denotes the regression coefficient of ξj on ηi; βij denotes the regression coefficient of ηj on ηi;ςi denotes the error variance of structure equation. The measurement equation of the SEM Model is:

$$X_i = \lambda_{xij}\xi_j + \delta_i \qquad [2]$$

$$Y_i = \lambda_{yij}\eta_j + \varepsilon_i \qquad [3]$$

Where; λxij denotes the regression coefficient of Xi on ξj; λyij denotes the regression coefficient of Yi on ηj; δi, εi denote measurement errors of exogenous [ξj] and endogenous [ηj] latent variables, respectively.

RESULTS

Reliability, Validity and Quality of the Constructed Model

The break-up of the demographic profile of the respondents is provided in Table 1. Table 2 lists the descriptive statistics for all the items on the questionnaire. For evaluating the measurement reliability and goodness of fit of the model, the final measurement scales for each latent variable are determined that satisfy the following criterion:[a]remove items with communalities lower than 0.3; [b] eliminate items with square multiple correlation[SMC] lower than 0.2; [c]do away with items with standardized factor loadings higher than 0.95; [d]put forward the modification index [MI]provided by LISREL8.70 package. Additionally, to test the internal consistent reliability Cronbach's α value is calculated by using SPSS 18.0 for Windows. We also conducted a confirmatory factor analysis [CFA] using 318 confirmatory samples to evaluate the construct validity of questionnaire. From the results of CFA [Table 3], all the factor loadings of observed variables on latent variables are significant and indicate a good model-fit.

Table 1 Demographic profile of respondents

Demographic profile	Percent
1. Age	
18-25 years	7.2
26-35 years	26.1
36-45 years	51.6
46-55 years	12.3
Above 55 years	2.8
2. Gender	
Male	73.9
Female	26.1
3. Marital status	
Married	82.1
Unmarried	17.9
4. Educational background	
Student	2.5
Graduate	44.0
Professional	49.1
Other	4.4
5. Annual income	
Below Rs 2 lakhs	5.0
Rs 2-5 lakhs	31.1
Rs 5-10 lakhs	38.7
Above Rs 10 lakhs	25.2
6. Disposable Income	
Below Rs 1 lakh	9.4
Rs 1-2 lakhs	12.3
Rs 2-3 lakhs	38.4
Rs 3-5 lakhs	22.6
Above 5 lakhs	17.3
7. Years of investment experience in equities	
Below 2 years	12.6
2-5 years	20.4
5-8 years	31.8
8-11 years	26.1
Above 11 years	9.1

For testing the validity of the model various fit indices refer to the ability of hypothetical theory model to closely correspond to the actual data. The fit indices and their values are summarized in the subsequent section and also provided in Appendix I.

Table 2 Descriptive statistics for items on the questionnaire

Item	Mean	Std. Deviation	Skewness	Kurtosis
LTR1	3.12	1.157	0.116	-0.977
LTR2	3.21	1.368	0.077	-1.360
LTR3	3.44	1.118	-0.319	-0.601
LTR4	2.98	0.963	0.230	-0.611
LTR5	3.23	1.168	0.099	-0.983
STR1	2.97	1.061	0.261	-1.301
STR2	3.07	1.431	0.048	-1.314
STR3	2.88	1.452	0.066	-1.347
STR4	2.89	1.057	0.325	-1.540
H1	2.89	1.057	0.325	-1.540
H2	2.78	1.110	0.583	-0.977
H3	3.02	1.099	0.069	-1.529
H4	3.11	1.585	-0.139	-1.511
O1	3.46	1.395	-0.277	-1.321
O2	3.40	1.298	-1.094	-0.314
O3	3.18	1.030	-0.498	-1.188
O4	3.52	1.540	-0.536	-1.252
R1	2.93	0.894	-0.071	0.125
R2	3.16	1.040	-0.139	-0.639
R3	3.00	0.976	0.061	-0.301
R4	3.26	1.265	0.044	-1.097

Table 3 Quality Measures for Latent Variables

SNo	Items	Cronbach's alpha	Standard factor loading	SMC
	Long term Investors	0.720		
1	Investing in equities is a better way to increase my wealth		0.659*	0.435
2	Long term profit[More than 5 years]		0.644*	0.415
3	I make all the important share investment decisions myself		0.652*	0.425
4	Fundamental Analysis [e.g Company Earnings, Management]		0.696*	0.485
5	Dividend Income		0.781*	0.610

Table 3 (Cont'd)

	Short term Speculative Investors	0.587		
1	I am willing to take high risk for high returns		0.737*	0.575
2	Short term profit[Less than 1 year]		0.722*	0.658
3	Fun/Excitement[like gambling]		0.285*	0.900
4	Pride/Ego		0.858*	0.755
	Herding, Social Contagion, Representative Heuristic	0.742		
1	Technical Analysis [e.g Share price movements, trading volume]		0.725*	0.525
2	Media		0.745*	0.554
3	Rely on Expert's Recommendation		0.749*	0.561
4	Information from friends and relatives		0.784*	0.614
	Over Confidence	0.649		
1	I am sure I can make correct investment decision		0.725*	0.312
2	My past profitable investments were mainly due to my specific investment skills		0.745*	0.538
3	The return rate of my investment is equal to or higher than the average return rate of the market		0.749*	0.581
4	I feel satisfied with my investment decisions in the past		0.784*	0.531
	Risk Aversion, Disposition Effect, Cognitive Dissonance	0.774		
1	I can buy hot stocks and avoid stocks that have performed poorly in the past.		0.681*	0.463
2	After a prior gain, I am more risk seeking than usual		0.862*	0.742
3	After a prior loss, I become more risk averse		0.752*	0.566
4	I avoid selling shares that have decreased in value and readily sell shares that have increased		0.792*	0.627

*|t|>2.58

Absolute Fit Indices

1. Chi Square value [$\chi2$]

   Among the SEM fit indices, the $\chi2$ is the only inferential statistic; all the others are descriptive. That is, only for the $\chi2$ we make statements regarding significance or hypothesis testing, and for the others, there exist only "rule-of-thumb" to assess goodness-of-fit. However, the $\chi2$ has its own problems. The most important of these is that the $\chi2$ is sensitive to sample size [Gerbing & Anderson 1988]. While it is important to have a large sample to enhance the precision of parameter estimation, it is the case that as N increases, $\chi2$ blows up. As a result, it has been suggested, that a model demonstrates reasonable fit if the $\chi2$ statistic adjusted by its degrees of freedom does not exceed 3.0 [Kline, 2004, 2010]:$\chi2/df \leq 3$.The model constructed in the present study can be considered reliable as the index of normed chi square = 2.13 [< 3] and Critical N = 211.43[> .200] and PNFI = 0.85[> .5].

2. Root mean square error of approximation [RMSEA]

   The RMSEA is the second fit statistic reported in the LISREL program and was first developed by Steiger and Lind [1980]. The RMSEA tells us how well the model, with the chosen parameter estimates would fit the population covariance matrix [Byrne, 1998]. RMSEA measures the discrepancy per degree of freedom, and a value ≤ 0.05 indicates close fit and ≤ 0.08 indicates a reasonable fit [Browne and Cudeck 1993].The SEM output reports the value of RMSEA = 0.058 suggesting a good fit.

3. Goodness-of-fit statistic [GFI]

   The Goodness-of-Fit statistic [GFI]is an alternative to the Chi-Square test and calculates the proportion of variance that is accounted for by the estimated population covariance [Tabachnick and Fidell, 2007]. By looking at the variances and covariances accounted for by the model it shows how closely the model comes to replicating the observed covariance matrix [Diamantopoulos and Siguaw, 2000]. This statistic ranges from 0 to 1 with larger samples increasing its value. A cut-off point of 0.90 has been recommended for the GFI. The GFI of the proposed model is 0.90and therefore is appropriate.

4. Root Mean Square Residual [RMR] and Standardised Root Mean Square Residual [SRMR]

   The RMR and the SRMR are the square root of the difference between the residuals of the sample covariance matrix and the hypothesised covariance model. Root Mean Square Residual [RMR] is the square root of the squared residuals, which is the mean of the residuals between observed and input matrices. The standardised RMR [SRMR] values range from zero to 1.0.The LISREL output indicates a RMR = 0.0030 and SRMR = 0.0020implying a well fit model as the values are less than .05.

Relative Fit Indices

1. Normed-fit index [NFI]

   The Normed Fit Index [NFI]Bentler and Bonett,[1980] statistic assesses the model by comparing the $\chi 2$ value of the model to the $\chi 2$ of the null model. The null/independence model is the worst case scenario as it specifies that all measured variables are uncorrelated. Values for this statistic range between 0 and 1 with values greater than 0.90 indicating a good fit. More recent suggestions state that the cut-off criteria should be NFI ≥ .95 [Hu and Bentler, 1999]. The NFI value of 0.99 substantiates that the constructed model has a good fit.

2. CFI [Comparative fit index]

   The Comparative Fit Index [CFI]Bentler, [1990] is a revised form of the NFI which takes into account sample size [Byrne, 1998] that performs well even when sample size is small [Tabachnick and Fidell, 2007]. A value of CFI ≥ 0.95 is presently recognised as indicative of good fit [Hu and Bentler, 1999]. This index is included in all SEM programs and is one of the most popularly reported fit indices due to being one of the measures least affected by sample size. The SEM output reports the value of CFI = 0.98 indicating a good fit.

Parsimony Fit Indices

1. The Parsimony Goodness-of-Fit Index [PGFI] and the Parsimonious Normed Fit Index [PNFI].

   The PGFI is based upon the GFI by adjusting for loss of degrees of freedom. Parsimonious Normed FI [PNFI] is defined as: [df proposed/df null]*NFI;

Higher values are better and this measure is most suited for comparison of alternative models with different degrees of freedom. This measure rewards parsimony. Substantial model differences are said to be when the difference between alternate models are 0.06 to 0.09.

Parsimonious GFI [PGFI] is defined as: [df proposed /1/2 *[No. of manifest variables]*[No of manifest variables+1]] *GFI. The value of PGFI lies in the range 0 to 1.0, and the higher the value, the higher the model parsimony is. The model constructed can be considered parsimonious as PNFI = 0.85[> .5] and PGFI = 0.70.

Relationship between Investment Decision making process and Behavioural Biases

The recent behavioural finance literature has proposed a number of behavioural factors. However, some previous studies typically focus on only one behavioural factor. One of our contributions is to examine different behavioural factors jointly, and measure how they relate to each other and to other investor characteristics. Figure 1 depicts the standardized output of the structural model. All the coefficients have statistically significant values.

The first variable "HERDING" has a coefficient of 0.05 for long term investors and 0.44 for short term investors. This construct has substantial positive loadings on Social Contagion and Representative Heuristic. The results suggest that this construct reflects that short term investors have a tendency to follow crowd more than long term investors. This finding is similar to the results of Moatemri Ouarda *et al*., (2013) that increased herding tendencies were mainly due to increased activity of short term speculative traders and the empirical work of Roszczynska-Kurasinska M. *et al*., (2012) that representativeness is positively associated with short term investors.

The second variable "OVER CON" has a coefficient of 0.15 for long term investors and 0.84 for short term investors. This result reveals that this construct reflects that the level of confidence and wishful thinking is high for short term investors when compared with long term investors. This result is akin to the outcomes of Abreu M & Mendes V (2011) that overconfident investors traded more frequently.

The third variable "RISK AVE" has a coefficient of 0.57 for long term investors and -0.01 for short term investors. This construct is positively associated with Disposition Effect and Cognitive Dissonance. The results indicate that long term investors are more conservative and risk averse than short term investors. This outcome coincides with Ben-David, I., & Hirshleifer, D. (2012) that for short prior holding periods, investors were much more likely to sell big losers than trivial ones and exhibited anti-disposition effect.

The hypothesized structural equation model allows us to verify the relationship between decision making process of long term and short term investors and behavioural biases. Our aim was to test the extent to which the investment decisions of the two categories of investors are influenced by behavioural factors viz., herding, over confidence and risk aversion.

The findings indicate that long term investors' decision making is significantly and positively influenced by risk aversion, Disposition Effect and Cognitive Dissonance. This finding may be due to the fact that fear of regret can play a major role in dissuading/ motivating someone to do something in order to avoid something else. [Ex: Defer selling stocks that have gone down and accelerate selling of stocks that have gone up]. However, long term investors tend to exhibit very low levels of overconfidence and weak herding tendency. This may be because of the fact that long term investors continue to search for information and search for alternatives with the motive of increasing their wealth in the long run. Short term investors exhibit more herding behaviour and it implies that they find it easier to follow the crowd and buy a popular stock; if it subsequently goes down, it can be rationalized as everyone else owned it. The modern theory of Collective behaviour used contagion to describe this transmission of thoughts, ideas or behaviour from one individual to an entire group of people. The contagion behaviour of collective behaviour is based upon the idea that moods and thoughts become contagious within certain types of crowds.

The short term decision making process directly and simultaneously contributes to over confidence, Social Contagion and Representative Heuristic whereas it has a negative effect on Risk aversion, Disposition Effect and Cognitive Dissonance. This is because, overconfident investors tend to overestimate their private information and it further leads to more aggressive trade. In other words, their attitude towards risk is consistent, regardless of whether their assets have appreciated or lost. Therefore a higher overconfidence implies lower risk aversion and the findings are consistent with this notion in the context of short term investors.

The measurement accuracy for each latent variable can be evaluated by the error variances for the observed items in the SEM model. For instance, there is an error variance of 0.67 on item LTR1 for long term investors. This result implies that 33% of the variance is explained by the latent variable, whereas the remaining 67% variance is explained by other factors. According to the estimates of the structure parameters, if risk aversion decreases by a standard deviation of one, over confidence tends to increase by a standard deviation of 0.20. Additionally, if over confidence increases by a standard deviation of one, herding tends to increase by a standard deviation of 0.58. Thus, this finding implies that decision making of investors; both long term and short term is influenced by behavioural biases by varying degrees.

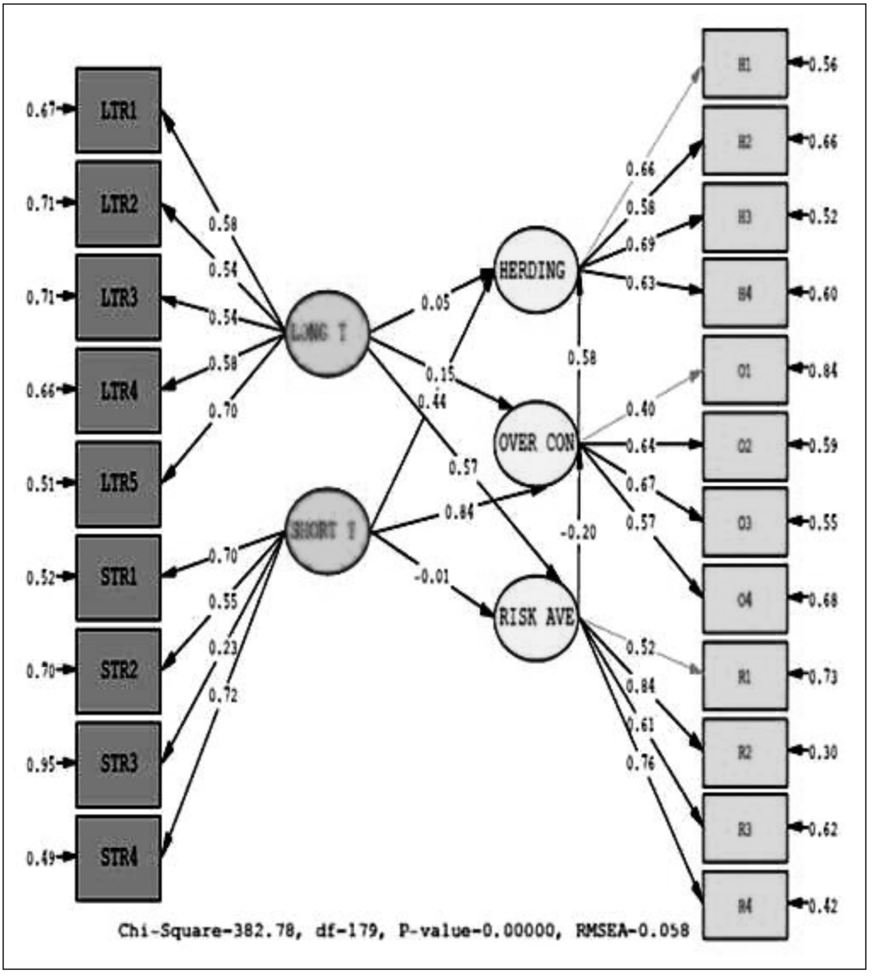

Figure 1 Structural model output

LIMITATIONS AND FUTURE RESEARCH

The research has the usual limitations of a survey study. First, the respondents are not randomly selected. While the respondents are selected to match the general population, those who join the survey may be analytically different in ways that limit the generalizability of the results. It is also possible that the preferences stated in surveys may differ from actual behaviour. For two reasons, we propose that the results of this research are relevant. First, the results support almost all the hypotheses, which were developed for the study. Second, an important question is whether the behavioural aspects that influence investing among the short term investors are different from the traits that influence investing among the long term investors. While the respondents were not required to provide information on how long they held individual stocks, information on their intentions towards long term/short term profits were collected, since it is highly correlated with investment decision making. Stock investors who focus on long-term capital appreciation are probably very different from day traders. Future research should compare and contrast the traits of those who have tendency to engage in different types of stock market participation. In addition, future research should investigate the characteristics of those who engage in high risk forms of intraday stock trading.

CONCLUSION

Behavioural biases and prospects are abundant in financial markets especially emerging markets like India. Local investors lack the analytical tools and are prey to rumours. Through a structural analysis on data collected from 318 Indian individual investors, this paper offers an additional reason: There is a higher degree of overconfidence, Herding, Social Contagion and Representative Heuristic behaviour among short term investors than those with a longer investment horizon. Furthermore, as the degree of risk aversion, disposition effect and Cognitive Dissonance becomes sufficiently large, the investment decision tends to become long term.

The awareness that investors could possess different opinions to preserve their sense of self-identity with respect to investment horizon may seem odd in a financial setting, but would not be astounding to several social psychologists. This explanation is consistent with several aspects of trading experiences of retail investors. Behavioural finance has investigated many aspects of investors' behaviour, and we can apply this groundwork to understand the perspectives of local investors. Considering the behavioural traits can lead to some approaches that investors should put into practice when investing in financial markets. The interrogation of what effects other behavioural aspects might have on investor preferences is commendable of future research.

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APPENDIX

Fit Indices and their acceptable Threshold levels

Fit Index	Acceptable threshold levels	Description	Reported values
Absolute fit indices			
Chi-Square $\chi 2$	Low $\chi 2$ relative to degrees of freedom with an insignificant *p* value [$p > 0.05$]	Inferential statistic, sensitive to sample size [Gerbing & Anderson 1985]	382.78
Relative $\chi 2$ [$\chi 2$/df]	$\chi 2$ statistic adjusted by its degrees of freedom [Kline, 2004]: Value of $\chi 2/df \leq 3$.	Adjusts for sample size.	2.13
RMSEA	Values less than 0.07 [Steiger, 2007]	Has a known distribution. Favours parsimony.	0.058
GFI	Values ≥ 0.90	Scaled between 0 and 1, with higher values indicating better model fit.	0.90
RMR	Good models have small RMR [Tabachnik and Fidell, 2006]	The average squared differences between the residuals of the sample covariances and the residuals of the estimated covariances.	0.003
SRMR	SRMR less than 0.08 [Hu and Bentler, 1999]	Standardized version of the RMR. Easier to interpret due to itsstandardized nature.	0.002
Incremental fit indices			
NFI	Values greater than 0.95	Assesses fit relative to a baseline model which assumes no covariances between the observed variables.	0.99
CFI	Values greater than 0.95	Normed, 0-1 range.	0.98
PNFI	Values greater than 0.5 [Sharma *et al*., 2005; McDonald and Marsh, 1990]	Non-normed, values can fall outside the 0-1 range. Favours parsimony. Performs well in simulation studies	0.85