

April 2022

Cognitive Biases of Trained Finance Professionals in India: An Exploratory Analysis

Labanya Prakash Jena
Xavier Institute of Management, labanyajena@gmail.com

Follow this and additional works at: <https://managementdynamics.researchcommons.org/journal>



Part of the [Cognitive Science Commons](#), and the [Portfolio and Security Analysis Commons](#)

Recommended Citation

Jena, Labanya Prakash (2022) "Cognitive Biases of Trained Finance Professionals in India: An Exploratory Analysis," *Management Dynamics*: Vol. 22: No. 1, Article 6: 43-51

DOI: <https://doi.org/10.57198/2583-4932.1299>

Available at: <https://managementdynamics.researchcommons.org/journal/vol22/iss1/6>

This Research Article is brought to you for free and open access by Management Dynamics. It has been accepted for inclusion in Management Dynamics by an authorized editor of Management Dynamics.

Cognitive Biases of Trained Finance Professionals in India: An Exploratory Analysis

Abstract

Cognitive biases among trained financial professionals may lead to mismanagement of investment decision-making or inadequate utilization of resources. Not many studies in this domain are available in the Indian context. The objective of the study is to find out the main cognitive biases among finance professionals in India. Using my diverse professional online networks, 162 trained finance professionals' survey responses are gathered for this study. I used Principal Component Analysis (PCA) method since it is suitable for this study. The PCA method allows to find out the critical group of factors incorporated in the questionnaire and derive the significant factors that have a meaningful impact on the subjects. Deploying principal component analysis (PCA), the paper finds that trained professional managers are exposed to diverse degrees of biases such as representative, confirmation, conservative, framing, hindsight, and availability biases. However, out of all such biases the representative bias is observed to be most prominent among the trained finance professionals in India. The findings of this study extend the scope to examine the effect of such cognitive biases on investment decision-making.

Keywords

Finance, education and training, cognitive biases, emerging market, India

Cognitive Biases of Trained Finance Professionals in India: An Exploratory Analysis

Labanya Prakash Jena

Doctoral Scholar, Xavier School of Management, XLRI, Jamshedpur

Abstract

Cognitive biases among trained financial professionals may lead to mismanagement of investment decision-making or inadequate utilization of resources. Not many studies in this domain are available in the Indian context. The objective of the study is to find out the main cognitive biases among finance professionals in India. Using my diverse professional online networks, 162 trained finance professionals' survey responses are gathered for this study. I used Principal Component Analysis (PCA) method since it is suitable for this study. The PCA method allows to find out the critical group of factors incorporated in the questionnaire and derive the significant factors that have a meaningful impact on the subjects. Deploying principal component analysis (PCA), the paper finds that trained professional managers are exposed to diverse degrees of biases such as representative, confirmation, conservative, framing, hindsight, and availability biases. However, out of all such biases the representative bias is observed to be most prominent among the trained finance professionals in India. The findings of this study extend the scope to examine the effect of such cognitive biases on investment decision-making.

Keywords: Finance, Education and training, Cognitive biases, Emerging market, India

1. Introduction

The psychological factors influence the decision-making of humans, including investors. There have been several empirical findings illuminate that psychological factors (cognitive and emotional biases) influence humans' decision making significantly, resulting in sub-optimal investment decision. Behavioral finance started in the 1970s but gained popularity in the 1990s with the development of psychology. In recent years, financial economists have been exploring this area unearthing earth new theories; practitioners have delved into this subject to optimize final decision-making for better performance. The advent of computing power, artificial intelligence, and machine learning further accentuated this area with the availability of several varieties of data available from various sources.

von Neumann and Morgenstern (1944), in their pioneering work on game theory and economic behavior, introduced the concept of subjective probability, which inspired researchers to work on behavioral economics and game theory. Their

insights also inspired researchers in finance who were finding it difficult to accept the rational hypothesis. Kahneman and Tversky (1974) groundbreaking work on behavioral finance developed the prospect theory, which gave origin to subsequent studies on behavioral finance. Shefrin and Statman (1994), Thaler (1985), Shiller (1995), Shleifer (2000) enriched the behavioral finance discipline further. They utilized the theories of psychology and other social sciences to shed light on the inefficiency of financial markets as well as explain the root cause of many stock markets anomalies such as bubbles, depression, scams, and market crashes. Their ideas have revolutionized the way the financial decision-making process is viewed. The evolution and the behavioral finance framework are depicted in Figs. 1 and 2.

Although researchers have found path-breaking theories to understand human behavior in financial decision-making, most of these studies have been undertaken in developed markets such as the United States and Europe. Since human behavior is influenced by the cultural setting of the region, the behavioral finance research conducted in the

Received 7 June 2022; revised 11 June 2022; accepted 5 July 2022.

Available online 22 August 2022

E-mail address: florian.hintz@mpi.nl.

<https://doi.org/10.57198/2583-4932.1299>

2583-4932/© 2022 The Authors. Published by Jaipuria Institute of Management. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

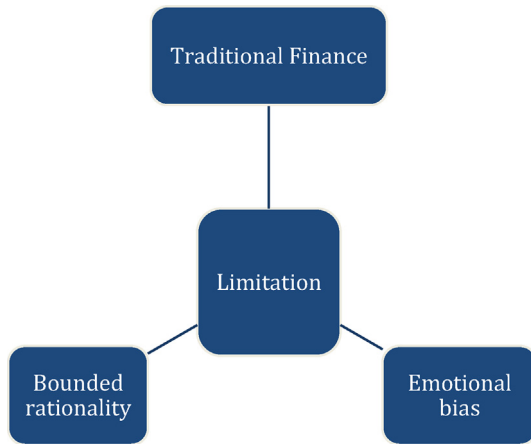


Fig. 1. Limitation of traditional finance.

developed market may not offer a proper explanation in the context of Asia, particularly India. Given cultural and sociological diversity differs in India from other markets, it reflects a need for further research on the behavioral biases of trained finance professionals. Moreover, the limited research undertaken in India so far on behavioral finance has focused on behavioral biases in general and concentrated on all the participants in the financial market. Nikiforow (2010) detected that there had been limited serious research conducted to understand the relationship between trained finance professionals and their investment behavior. These findings limit the understanding of cognitive biases of trained financial professionals, who are not supposed to exhibit cognitive biases since they are trained to avoid faulty reasoning. Identifying the critical cognitive biases and moderating them thereafter can help finance professionals in making better investment decisions, thereby enabling better capital allocation.

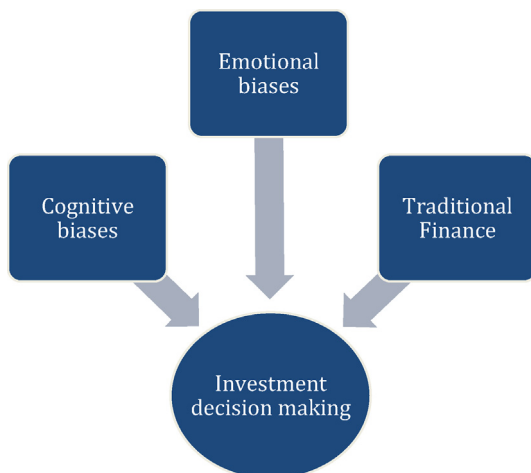


Fig. 2. Influence of psychology on investors.

The scope of this research paper is to explore whether trained finance professionals exhibit cognitive biases in India and identify the critical cognitive biases they exhibit. The study will encompass a granular analysis of all the cognitive biases individuals exhibit in their decision making. My objective is to examine the relationship between cognitive biases and investment decision making of trained finance professionals. The findings will help to determine the most influential cognitive biases and measure the impact of those biases in investment decision making. The findings will pave the way for developing investment tools and training to moderate these prominent cognitive errors.

The empirical findings on behavioral finance suggest that familiarity with a subject influence investment behavior. Trained finance professionals study finance and investment in their educational curriculum, which theoretically makes them less prone to cognitive biases. Therefore, they are less exposed to cognitive errors in their decision making. My hypothesis is derived from this logic. The hypothesis of this paper is *H1: Trained finance professionals in India do not exhibit cognitive biases in their investment decision making.*

I used a survey instrument to understand whether trained finance professionals exhibit cognitive biases in their investment decision making. I also examined whether there is any systematic cross-sectional variation exists in their cognitive biases. Through this research paper, I contribute to behavioral finance literature that suggests investors exhibit cognitive biases. Identifying the key cognitive biases will help investment management professionals to moderate these biases and can lead to better investment decisions.

I defined trained finance professionals as those who have studied finance in school, college, business school, or pursued professional education. The courses I considered are Master's in business administration (MBA), Chartered Financial Analyst (CFA), Commerce and economics Graduates, Chartered Accountant, Company Secretary, Cost Accountant, and Master's in Finance.

I sent the survey to 439 survey respondents who are knowledgeable about financial and investment theories. The respondents are based in various parts of India, mostly concentrated in Mumbai and New Delhi—the two locations in India where trained finance professionals are mostly working. I found that my survey respondents do not give any indication of significant cognitive biases of trained finance professionals in India. The respondents exhibit Representative Bias as the most influential cognitive biases followed by Confirmation,

Conservative, Framing, Hindsight, and Availability biases. The survey result also shows that there is high variability among all the factors, which indicates there is no consistency in cognitive biases among trained finance professionals.

2. Methodology and research design

2.1. Survey development

In the empirical finance literature, researchers are extensively using surveys as a tool. Selltiz et al, (1976) opined that literature research, experience surveys, and insight stimulating yield good result in exploratory research. I prepared the questions with an objective to measure the intensity of the responses to the questions. I developed questions whose answers are difficult to be captured from archival data. I borrowed the questions from the existing empirical literature on behavioral science that captures the cognitive biases. I borrowed most of the questions from behavioral science studies conducted in India to make them reliable and valid to mitigate undesirable properties. Since many measures have been taken in a different culture, I assessed construct equivalence to remove the influence of cultural perspective. I also iterated the survey questions before conducting the survey to verify the content validity of the instruments chosen in the survey, as suggested by DeVellis (1991). I revised the survey questions based on the feedback from one academician and two practitioners in the investment management industry. I used the statistical correlation technique to test the criterion and construct validity. My result explains that there is no multicollinearity among the variables used in the survey. Hair and Anderson, et al. (1995) suggest as a “rule of thumb,” the correlation of 0.8 among the variable is acceptable. The correlation matrix of the survey does not indicate any such problems. I used Cronbach’s Alpha method to test the reliability of the survey instrument. The data sets in the survey suggest that the Cronbach’s Alpha is more than 0.5 for all the variables, which shows the survey instruments are valid and reliable.

2.2. Survey delivery

I distributed the survey questions among trained finance professionals through emails and professional Whatsapp groups. All the members of the professional Whatsapp groups are trained finance professionals. The total number of individuals in the Whatsapp Group is 482. I also used my professional, LinkedIn, and alumni network, and references to identify respondents. I sent 212 emails to this category of

respondents. I obtained 194 responses from the survey; I excluded participants who have not completed the survey and found logical inconsistencies in their responses as proposed by Meade and Craig (2012). I removed 32 responses in this process and considered 162 responses in my study.

2.3. Respondent characteristics

Table 1 provides a profile of sample respondents. The largest numbers of respondents are MBAs (55.6%), followed by CFAs (37.0%). It is noteworthy here a large number of investment professionals in the stock market are MBA and CFAs. A small number of respondents are CA/CS/CMA (3.7%) and Commerce and Economics Graduates (3.7%). A large number of respondents are Male (83.3%). A large number of respondents are in the age group of 30–40 (63%), followed by the 40–50 age group. For exploratory analysis, a sample of 150 should be adequate to get a correct result; however, the interrelations between the variables must be reasonably strong, as recommended by Guadagnoli and Velicer (1988). I also focused on the ratio of the number of participants to the number of measures in factor analysis. Comrey and Montag, 1982 and Gorsuch (1983) suggested that a minimum of 5–10 participants per measure would yield a reliable result (see Table 2) (see Tables 3 and 4).

2.4. Scale of measurement

The value of constructs decides the way the concept is measured. Selecting a proper period of scale is paramount to find the correct result. I used Likert scales, which gives the options to measure the

Table 1. Sample respondents profile.

Age	Count	%	Mean	Median	S.D.
Male	135	83.3%			
Female	27	16.7%			
Total	162				
Age Group					
30–40	102	63.0%	35.0	33.2	5.8
20–30	25	15.4%			
40–50	29	17.9%			
50–60	6	3.7%			
Total	162				
Education					
MBA	90	55.6%			
CFA	60	37.0%			
CA/CS/CMA	6	3.7%			
Economics/ Commerce (UG/PG)	6	3.7%			
Total	162				

Source: Findings based on Author's analysis.

Table 2. Descriptive statistics.

	N	Minimum	Maximum	Mean	Std. Deviation
Representative Bias	164	1.00	5.00	3.6037	1.78136
Availability Bias	164	5.00	10.00	7.1890	1.50080
Hindsight Bias	164	2.00	10.00	6.4939	2.19452
Framing Bias	164	3.00	15.00	11.2256	3.61206
Conservative Bias	164	3.00	15.00	10.8720	3.57935
Confirmation Bias	164	3.00	15.00	10.3476	2.89403

Source: Findings based on Author's analysis.

various degrees of the responses. The length of the scale is mostly four, which is used in the study, which closely aligns well with the suggested range (Five is the highest biased while one is lowest biased). I used two categories of scales in this paper: the agree-disagree scale and the item-specific scale. The scale helps in capturing the extent to which people attach importance to their behavior. I provided enough labels so that respondents do not feel

that their behavior is not normal. I used four or more items per factor in the factor analysis to ensure adequate identification of factors suggested by Comrey and Montag, 1982, and Gorsuch (1988).

2.5. Data analysis techniques

I used statistical packages like SPSS and M.S. Windows (Excel) software to analyze the data and summarize the findings. The data is categorized into three groups: gender, education, and age group. I used descriptive statistics, sampling adequacy, reliability analysis, and exploratory factor tools.

I used the Principal Component Analysis (PCA) method since it is suitable for this study as recommended by Kolenikov and Angeles et al, (2004). The PCA method allows to find out the critical group of factors incorporated in the questionnaire and derive the significant factors that have a meaningful impact on the subjects. I have used the PCA method to find out the vital cognitive biases influencing trained

Table 3. One-sample test.

	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
V4 Availability Bias	59.751	163	.000	3.66463	3.5435	3.7857
V5 Availability Bias	47.021	163	.000	4.06098	3.8904	4.2315
V6 Availability Bias	46.003	163	.000	3.52439	3.3731	3.6757
V7 Availability Bias	44.800	163	.000	3.86585	3.6955	4.0362
V8 Availability Bias	30.539	163	.000	3.70732	3.4676	3.9470
V9 Conservative Bias	38.030	163	.000	3.67683	3.4859	3.8677
V10 Conservative Bias	30.614	163	.000	3.48780	3.2628	3.7128
V11 Conservative Bias	36.171	163	.000	3.37195	3.1879	3.5560
V12 Conservative Bias	32.314	163	.000	3.57927	3.3605	3.7980
V13 Anchoring Bias	29.010	163	.000	3.24390	3.0231	3.4647
V14 Anchoring Bias	51.787	163	.000	3.06098	2.9443	3.1777
V15 Anchoring Bias	41.270	163	.000	3.28659	3.1293	3.4438
V16 Anchoring Bias	24.822	163	.000	3.15244	2.9017	3.4032
V17 Framing Bias	29.297	163	.000	3.65854	3.4119	3.9051
V18 Framing Bias	38.314	163	.000	3.74390	3.5510	3.9369
V19 Framing Bias	30.951	163	.000	3.82317	3.5793	4.0671
V20 Framing Bias	30.510	163	.000	3.80488	3.5586	4.0511
V21 Hindsight Bias	31.184	163	.000	3.15244	2.9528	3.3521
V22 Hindsight Bias	33.394	163	.000	3.44512	3.2414	3.6488
V23 Hindsight Bias	32.598	163	.000	3.34146	3.1391	3.5439
V24 Hindsight Bias	35.956	163	.000	3.58537	3.3885	3.7823
V25 Illusion of Control Bias	24.718	163	.000	3.20122	2.9455	3.4569
V26 Illusion of Control Bias	45.384	163	.000	4.07927	3.9018	4.2568
V27 Illusion of Control Bias	25.763	163	.000	3.09756	2.8601	3.3350
V28 Confirmation Bias	48.833	163	.000	3.63415	3.4872	3.7811
V29 Confirmation Bias	36.309	163	.000	3.42683	3.2405	3.6132
V30 Confirmation Bias	33.615	163	.000	3.28659	3.0935	3.4796
V31 Representative Bias	30.740	163	.000	3.72561	3.4863	3.9649
V32 Representative Bias	33.218	163	.000	3.65244	3.4353	3.8696
V33 Representative Bias	31.416	163	.000	3.45122	3.2343	3.6681
V34 Representative Bias	25.907	163	.000	3.60366	3.3290	3.8783

Source: Findings based on Author's analysis.

Table 4. Principal component analysis.

Total Variance Explained							
Component (Bias)	Initial Eigenvalues	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
Representative	3.063	3.063	18.016	18.016	2.559	15.054	15.054
Confirmation	2.500	2.500	14.707	32.724	2.179	12.815	27.869
Conservative	1.968	1.968	11.576	44.300	2.153	12.667	40.536
Framing	1.855	1.855	10.913	55.213	2.024	11.909	52.444
Hindsight	1.321	1.321	7.772	62.985	1.517	8.923	61.367
Availability	1.202	1.202	7.069	70.054	1.477	8.687	70.054

Source: Findings based on Author's analysis.

financial professionals. I followed three criteria to conduct PCA analysis: the Eigen value-one, the screen test, and the proportion of variance accounted for as proposed by [Cattell \(1966, pp. 245–276\)](#) and [Stevens \(1986\)](#). I also used orthogonal rotation, which is commonly used for factor analysis (25, 33%), and retained factors having Eigenvalues higher than one.

I used Kaiser-Meyer-Olkin (KMO) measures of sample adequacy and Bartlett's Test of Sphericity to determine the suitability of data for factor analysis. [Hutcheson and Sofroniou \(1998\)](#) argues that KMO value of 0.5 is sufficient to conduct a factor analysis. Bartlett's test of Sphericity is 0.000, which indicates that there is a strong relationship between the variables. The results from these tests are given in the table below. I used ChiSquare to test the reliability of the data set; the smaller the Chisquare value, the better it fits with the model. [Carmines and McIver \(1981\)](#) suggested that if the Chi-Square value is 2–3 times greater than the degree of freedom, then the sampling is acceptable. However, the closer the Chi-Square value to the progress sample, the model fit would be better; the ratio of 5 to 1 is a useful rule of thumb. The sampling adequacy of my survey yields a KMO of 0.671, Bartlett's test of 0.000, and the Chi-Square value is more than 3 times the degree of freedom.

3. Literature review

The traditional financial theories have a normative approach to financial decision making, which is very much prescriptive in nature. It describes how an investor should take an investment decision. The real-world investment decision-making process is influenced by other factors beyond the scope of traditional finance. The assumptions of traditional economics are also not realistic: humans are not rational at all-time, and each human does not have the same level of intelligence. Emotional swing (optimism and pessimism), heuristics, greed, and fear influence investment decision-making, which are not captured by traditional financial theories.

The origin of behavioral finance goes back to the 1950s, just after the emergence of modern financial

theories, with the advancement of cognitive psychology. [Simon \(1955\)](#) introduced the principle of bounded rationality, which illustrated the limitation of human minds in solving problems. However, behavioral finance got its due recognition in the academic discipline in the 1970s. During this period, the prospect theory of [Kahneman and Tversky \(1978\)](#) brought the attention of academicians to behavioral finance and led a solid foundation for further research in this field. [Kahneman and Tversky \(1978\)](#) questioned the validity of utility theory and demonstrated cases where axioms of utility theory are violated. The prospect theory brought the concept of loss aversion—a twist to the principle of risk aversion. The loss aversion concept illustrates that people react at losses and gains—investors are risk-averse in gains (concave) and risk-averse in losses (convex). This concept contrasts with modern financial theories, which considers only risk aversions irrespective of losses and gains. Framing, another application of prospect theory, illustrates how the change in words and situations influence human behavior. The prospect theory led gave birth to the mental accounting and disposition effect. [Shefrin and Statman \(1985\)](#) made an argument that investors hold their loss-making positions too long while selling their profit-making positions too early.

Traditional finance theorist follows Bayes' theorem, which offers a way to incorporate new information in decision making. [Bondt and Thaler's \(1985\)](#) concept of overreaction questions the correct usage of Bayes' theorem in-stock selection. Their research findings suggest that investors overweight recent information while underweight prior knowledge. These findings challenge the validity of the efficient market hypothesis—precise incorporation of new information in investment decision making at all the time. This finding is supported by [Barberis et al. \(1997\)](#) in their paper, "A model of investors sentiment." Their study suggests that intelligent investors can generate higher returns by leveraging overreaction and under reaction of the market without taking additional risk.

The concept of cognitive biases is derived from the theory of cognitive dissonance, developed by [Festinger, Riecken, and Schachter \(1955\)](#). The method of cognitive dissonance draws its findings from an experiment, which suggests that their inconsistencies between human actions and beliefs—human activities are not always guided by their beliefs. Cognitive biases were initially captured by behavioral finance theorists [Kahneman and Tversky \(1974\)](#) in their seminal work on heuristics and biases. They illustrated how cognitive biases such as anchoring, overconfidence, hindsight bias, representativeness, and herding influence investors' investment decision making. Humans do not use all the information—either when information is overloaded or incomplete—they use conventional wisdom, aka heuristic, primarily based on their personal experiences whenever they encountered a high degree of uncertainty and choice. The lack of time or ability or willingness to commit so much time to analyze all the available information makes humans take a simpler route to make a decision. [Plous \(2007\)](#) opined that Even the decision-maker is aware that the decision would yield a suboptimal result, they would be happy with the arrangement as long as the decision is satisficing—a minimum threshold level of meeting the expectation of the decision-maker.

Cognitive biases can be divided into two categories: Belief perseverance and information processing. Belief perseverance is sticking to earlier beliefs or opinions, even if the views are no more logical or rational. This Bias leads to memory (incorrect recall of information or complete loss of data), statistical and data processing errors. In general, belief perseverance is a tendency to incline to existing beliefs without any proper logic or rationale. Statistical and information-processing errors continue to justify existing beliefs. The second category of cognitive error has to do with “processing errors,” describing how information may be processed and used illogically or irrationally in financial decision making.

Belief perseverance is a psychological thought derived from the theory of cognitive dissonance. According to [Festinger \(1957\)](#), cognitive dissonance is a person's mental discomfort when they receive new information, which conflicts with their existing belief. CFA Institute (2015) further argued that to reduce their psychological pain, they consider that information that confirms their current beliefs or modifies the information to strengthen their Representativeness, Illusion of Control, and Hindsight biases.

Information-processing error is related to incorrect processing of information; this leads to illogical or irrational use of processed information.

Information-processing Bias can be divided into four categories: Anchoring and Adjustment, Availability, Mental Accounting & Framing.

4. Findings

4.1. Preliminary analysis

My survey reveals the survey respondents' responses to the questions related to influence of cognitive biases on their decision making. The independent variables used in the survey are Representative, Availability, Hindsight, Framing, Conservative, Confirmation, Anchoring and Adjusting, and Illusion of Control biases. The dependent variable is investment decision making.

The preliminary analysis of the survey does not give any indication of significant cognitive biases of trained finance professionals in India; however, the survey results show that there are moderate cognitive biases. The survey suggests that Representative bias is the most influential cognitive biases among the trained finance profession, while Hindsight is the least cognitive biases. The survey result also shows that there is high variability among all the factors, which indicates there is no consistency in cognitive biases among trained finance professionals. My preliminary analysis of survey findings is not revealing the significant cognitive biases affecting the respondents. Hence, I used advanced analytical methods to derive the key cognitive biases influencing the respondents.

Social science researchers use a single sample *t*-test to compare the mean of a single sample of scores with the mean. The One-sample test suggests that the mean difference is high, which indicates that there is a difference between value and true mean; the true mean, in this case, is 3. The alternative hypothesis assumes that some variation exists between the true mean (μ) and the comparison. Also, the mean difference is more than 3. Besides, the table also suggests that at a 95% confidence level, the lower and upper limit in most of the items is more than the true mean (3). My findings suggest that trained finance professionals exhibit cognitive biases in India.

4.2. Principal component analysis

The principal confirmatory analysis provides some useful insights into the dataset. The number of factors whose Eigenvalue is more than one is rotated. The factor analysis extracts 13 cognitive components, but only six components I retained for rotation and interpretation, as these five components are judged sufficient to explain the significant data variance and also qualified the above-

mentioned criteria for solving the number-of-components problem. The cumulative variance of these 11 factors is 70.05%, which is which meets the required minimum cumulative variance of identified factors-70% (Henson & Kyle Roberts, 2006; Costello & Osborne, 2009, pp. 131–146).

The PCA analysis derives six meaningful cognitive biases are: Representative, Confirmation, Conservative, Framing, Hindsight, and Availability biases. The total variance accounted for by the components with Eigenvalue greater than one is 70.05%, which is sufficiently significant, and the remaining variance is explained by other variables. Among the six components, the first two components—Representative bias and confirmation bias—accounts for around 28% of the variance; these cognitive biases primarily influence investment behavior in investment decision making. The result negates the hypothesis that confirmation and illusion of control are the two key cognitive biases affecting investment behavior. I am discussing below details of the findings of the survey.

Representative bias is the first component of my Principal Component Analysis (PCA). It seems the respondents exhibit that they tend to use their past experiences and initial classifications when categorizing new information. They place a higher weight on the original classification as they believe that the original classification is appropriate even if the context might have changed. My result shows that the respondents demonstrate the heuristic judgment of individuals. They are likely changing portfolios based on short-term results and sell the stock even if it is not fundamentally justified.

Confirmation bias is the second component of my Principal Component Analysis (PCA). My result shows that the respondents selectively look for information that confirms their beliefs and ignores information that is contradictory to their beliefs. They are likely overweight on information that confirms their beliefs and underweights information that refutes their beliefs since contradictory information creates mental conflict in their minds.

The survey respondents display conservative bias. This findings indicate that they do not change their belief and do not properly incorporate new information in their investment decision making. This is against the Bayes' theorem—change in belief with the release of new information. It is likely they do not change their views on their stocks even if there is enough signal of change (Barberis et al., 1997).

The fourth component is Framing bias. Our findings suggest that the formulation of choices and personal characteristics of my survey respondents influence their choices. Their choices are influenced

by their subjective opinions, which may not be significant in the context. Framing bias could lead the respondents to wrong interpretation of riskiness, wrong investment choice, and excessive trading turnover.

My survey reveals that the respondents display hindsight bias. It appears that they tend to believe that past events are reasonably predictable. They seem to overestimate their knowledge of an event, which leads to an increase in the predicted likelihood of the event. Hussain et al.'s (2013) study on hindsight bias in emerging markets suggests that investors in emerging markets are selective in their memory and exhibit undue confidence in their forecasts.

The last component derived from my survey analysis is availability bias. My survey result shows that the respondents tend to overweight easily available and retrievable information, ideas, or thoughts in probability estimates makes the decision erroneous. Schwarz (1998) opines that individuals inflate the frequency and importance of recent easily available instances, which influences judgments and decisions. Availability bias leads to limited investment avenues, choosing stocks or funds based on advertising, and sub-optimal asset allocation.

5. Way forward

Respondents may be aware of behavioral biases, so they could consciously reply to the queries. The researcher has not attempted to differentiate the biases of day traders and long-term investors. The biases of these two sets of investors could be different. This is primary research through an on-line survey. However, an experiment would have yielded a better result.

The behavioral biases of long-term investors could be different from day traders and investors with a short investment horizon. It will be interesting to study the behavioral biases of these two kinds of investors. The behavioral biases could be varied among different age groups. It is important to note that diverse age groups have different views, perceptions, and behavior. The behavioral biases of each group of investors could be different. There has been limited research conducted on behavioral biases among various age groups. A study on this subject would discover some interesting findings. It is commonly understood that experienced investors control their emotions and seldom exhibit cognitive biases better than less experienced investors. This narrative warrants comprehensive research to discover whether experienced professionals in the financial market really manage behavioral biases better than less experienced professionals.

Appendix

Table A1. Variable definitions.

Variable	Definition	Survey Question No.
Conservatism	Conservatism bias is related to unchanged belief and lack of proper incorporation of new information in decision making.	V9–V12
Confirmation	Confirmation bias is exhibited when an individual selectively looks for information that confirms their beliefs and ignores information that is contradictory to their beliefs.	V28–V30
Representative	Representativeness bias is exhibited when individuals incline to use their past experiences and original classifications when classifying new information.	V31–V34
Illusion of Control	The illusion of control is a bias when individuals believe that they have control of the result or at least influence the result; in fact, they do not have any control.	V25–V27
Hindsight	Hindsight bias is related to selective memory of past events leading to an increase in predictive ability.	V21–V24
Anchoring and Adjustment	Anchoring and Adjustment bias is related to an individual's inclination towards making a data point or information as a base and then adjusting the base in response to new information.	V13–V16
Availability	Availability bias is a form of information-processing related to taking the heuristic approach in decision making. The tendency of individuals to overweight easily available and retrievable information, ideas, or thoughts in probability estimates makes the decision erroneous.	V4 – V8
Framing	Framing bias is related to choosing a choice based on how the choices are framed.	V17–V20

Table A2. KMO and Bartlett's test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.671
Bartlett's Test of Sphericity	Approx. Chi-Square df Sig.	1486.218 465 .000

Table A3. Reliability statistics.

Cronbach's Alpha	N of Items
.732	31

Table A4. Item–total statistics.

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item–Total Correlation	Cronbach's Alpha if Item Deleted
V4	105.7317	185.928	.216	.728
V5	105.3354	183.574	.213	.727
V6	105.8720	185.769	.166	.730
V7	105.5305	182.275	.257	.725
V8	105.6890	177.160	.280	.723
V9	105.7195	181.123	.256	.725
V10	105.9085	179.298	.249	.725
V11	106.0244	186.736	.092	.734
V12	105.8171	188.764	.010	.740
V13	106.1524	183.725	.139	.732
V14	106.3354	188.997	.077	.733
V15	106.1098	190.835	–.025	.738
V16	106.2439	179.768	.201	.729
V17	105.7378	174.600	.332	.719
V18	105.6524	180.878	.259	.725
V19	105.5732	179.142	.225	.727
V20	105.5915	174.022	.347	.718
V21	106.2439	181.486	.230	.726
V22	105.9512	174.218	.436	.714
V23	106.0549	183.377	.171	.730

(continued on next page)

Table A4. (continued)

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item–Total Correlation	Cronbach's Alpha if Item Deleted
V24	105.8110	182.081	.217	.727
V25	106.1951	176.367	.274	.724
V26	105.3171	183.482	.204	.728
V27	106.2988	179.119	.235	.726
V28	105.7622	184.710	.214	.727
V29	105.9695	180.447	.285	.723
V30	106.1098	181.350	.245	.726
V31	105.6707	174.001	.361	.717
V32	105.7439	174.830	.386	.716
V33	105.9451	178.764	.277	.723
V34	105.7927	162.926	.551	.701

References

- Barberis, N., Shleifer, A., & Vishny, R. W. (1997). *A model of investor sentiment*.
- Bondt, Werner, F. M. De, & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3), 793.
- Carmines, E. G., & McIver, J. P. (1981). Analyzing models with unobservable variables. In G. W. Bohrnstedt, & E. F. Borgatta (Eds.), *Social measurement: Current issues* (pp. 65–115).
- Cattell, R. B. (1966). *The scree test for the number of factors* (Vol. 1966). Multivariate Behavioural Research.
- Comrey, A. L., & Montag, I. (1982). Comparison of factor Analytic results with two-choice and seven-choice personality item formats. *Applied Psychological Measurement*, 6(3), 285–289.
- Costello, A. B., & Osborne, J. W. (2009). *Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis* (Vol. 2009). Pan-Pacific Management Review.
- DeVellis, R. F. (1991). *Scale development: Theory and applications" applied social research methods series* (Vol. 26). Newbury Park, CA: Sage Publications.
- Festinger, L. (1957). *A theory of cognitive dissonance*. Evanston, Ill: Row: Peterson.
- Festinger, L., et al. (1955). *When prophecy fails*.
- Gorsuch, R. L. (1983). *Factor analysis* (2nd ed.). Hillsdale, NJ: Erlbaum.
- Guadagnoli, E., & Velicer, W. F. (1988). Relation to sample size to the stability of component patterns. *Psychological Bulletin*, 103(2), 265–275.
- Hair, J., Anderson, R., et al. (1995). *Multivariate data analysis*. New Jersey: Prentice-Hall Inc.
- Henson, R. K., & Kyle Roberts, J. (2006). Use of exploratory factor analysis in published research: Common errors and some comments on improved practice. *Educational and Psychological Measurement*, 393–416.
- Hutcheson, G., & Sofroniou, N. (1998). *The multivariate social scientist: A non-mathematical guide*. Sage Publications.
- Kahneman, D., & Tversky, A. (1978). On the interpretation of intuitive probability: A reply to Jonathan Cohen. *Cognition*, 7(4), 409–411.
- Kahneman, D., & Tversky, A. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157), 1124–1131.
- Kolenikov, S., & Angeles, G. (2004). *Use of discrete data in PCA: Theory, simulations, and applications to socioeconomic indices*. Chapel Hill, N.C. Carolina Population Center MEASURE Evaluation, University of North Carolina at Chapel Hill
- Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods*, 17(3), 437–455.
- Nikiforow, M. (2010). Does training on behavioural finance influence fund managers' perception and behaviour?. Taylor & Francis Journals *Applied Financial Economics*, 20(7), 515–528.
- Plous, S. (2007). *The psychology of judgment and decision making*. McGraw-Hill Higher Education.
- Schwarz, N. (1998). Accessible content and accessibility experiences: The interplay of declarative and experiential information in judgment. *Personality and Social Psychology Review*, 2(2), 87–99.
- Selltiz, C., et al. (1976). *Research methods in social relations: Published for the society for the psychological study of social issues (SPSSI)*. Holt Rinehart & Winston.
- Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3), 777.
- Shefrin, H., & Statman, M. (1994). Behavioral capital asset pricing theory. *The Journal of Financial and Quantitative Analysis*, 29(3), 323.
- Shiller, R. J. (1995). Conversation, information, and herd behavior. In *Cowles foundation discussion papers 1092, cowles Foundation for Research in economics*. Yale University.
- Shleifer, A. (2000). *Inefficient markets: An introduction to behavioural finance*. Oxford University Press U.K.
- Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99.
- Stevens, J. (1986). *Applied multivariate statistics for the social sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates.
- Thaler, R. (1985). Mental accounting and consumer choice. *Marketing Science*, 4(3), 199–214.
- von Neumann, J., & Morgenstern, O. (1944). *Theory of games and economic behavior*. Princeton: Princeton University Press.