

Impact of Behavioural Disposition on Portfolio Investment Decisions of Individual Investors - A Structural Analysis

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Abstract

In the past two decades, behavioural finance, a new criterion of finance gained power on the basis of traditional finance. An ongoing debate between behavioural theorists and traditional theorists provides horizon for interrogation into the changing landscape of investment behaviour. Behavioural finance deals with the influence of psychological; factors on investment decisions. It diverges from the presumption of rationality and can describe how an investor takes investment decisions. In the alternating investment scenario and extreme dynamism in the capital market, investors do not adhere to rational thinking and reflect several dispositions. Therefore, studying how psychology plays a significant role in investment decisions becomes important. A structured questionnaire on impact of behavioral biases on investment decisions of individual investors on 5 point Likert scale was prepared and responses were collected from investors who make their own investment decisions. The paper identified through Confirmatory Factor analysis (CFA) and afterwards through Structural Equation Model (SEM) that Herd Mentality, Overconfidence, Disposition, Mental Accounting Anchoring, Representativeness, Loss Aversion and Regret Aversion are a few biases affects the portfolio investment decisions of individual investors.

Keywords: Behavioural Finance, Behavioural Disposition, Portfolio Investment Decisions, Confirmatory Factor Analysis, Structural Equation Model

Introduction

In the middle of 1950s, the field of finance has been administered by the standard finance model developed by the economist of the University of Chicago. The basic assumption of the standard finance model is that people are rational. These theories are built on the presumptions that investor behaves rationally and stock and bond markets are efficient. As the financial economist were presuming that people (investors) behaved rationally when making financial decisions, psychologists have found that economic decision are built in an irrational manner, so they challenge this assumption of standard finance. Psychological error and extreme emotional bias can make investors to make bad investment decisions, thereby meaning that they act in irrational manner. Over the past decade, field of behavioral finance has transpired to consider how personal and social psychology impact financial decisions and behavior of investors in general.

Behavioural Finance

Behavioral finance is a new perceptive to financial markets that has become a subject of notable interest to investment group. The field of Behavioural finance seeks to apprehend and define investor decisions by amalgamating topics of Psychology and investing at a micro level, i.e. the decision making process of individuals and groups, and at a macro level where the role of financial markets is contemplated. In everyday business life, people usually take decision, these decisions might have varies outcomes.

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Impact of Behavioral Finance in Decision Making

Behavioural finance seeks to find out how investor's psychology affects investment decisions. Investors financial decisions are influenced by various heuristics and prospect biases and their emotions affects their investment decisions profoundly. Generally, the investor's behavior deviates from making rational or logical decisions and leans towards being influenced by different behavioral dispositions. These biases impact the investor's rationality in investment decision-making.

Review of Literature

Sewell (2007), Srivastava Aman (2007), Gilovich, Thomas and Griffin Dale (2002), Fromlet (2001), Gervais and Odean (2001), Hirshliefer and Luo (2001), Thaler (1999), Benos (1998), Linter (1998), Olsen (1998), Kyle and Wang (1997) described behavioural finance as a scientific combination of psychology and finance which means that the weight is on psychology based knowledge at the individual level and financial markets findings. It is an integration of classical economics and financial theories within studies investigating psychology and decision making. It studies the influence of psychological happening on financial behavior and tried to explain why and how people make apparently irrational or unreasonable decisions when they save, invest, spend and borrow money. It is an emerging area in the field of financial research, which is at present dominated by theories and theoretical models. This area of behavioral finance borrows the theories from psychology, sociology, and other behavioral sciences to examine the behavioral aspects of the stock market and the investors.

Lakshmi, Visalakshmi, Thamaraiselvan, and Senthilarasu (2013), Iyer and Bhaskar (2002) conducted a research to find as to what degree long term and short term stock investors share different behavioural features. A structural model is employed to compare the features of the investors and examine how investment decision making and behavioural biases are interrelated, as well balanced the relative differences of behavioural biases such as Herding, Representativeness, Overconfidence, Risk Aversion, Disposition Effect and Cognitive Dissonance. Recognition of behavioral characteristics commonly related with investment tenure helps in providing

judgments and framing trading strategies. The cognitive effect of investment decision making among investors is measured through a sampling survey of 318 respondents. Structural Equation Modeling [SEM] and path analysis is performed on how investment decision making and the behavioral dispositions are correlated. Analytical results show that the structural path model closely fits to the sample data, implying the role of behavioral biases in investment decision making among individuals. The study also depicts that long term and short term investors prominently differ in behavioral characteristics. Iyer and Bhaskar attempted to identify the various psychological factors affecting the market of Chennai and the various other factors contributing to the market meltdowns and upsurges. Interviews of the leading brokers and the market players in Chennai were done. The authors gave the theoretical explanation of the various psychological facets like fear, greed, overconfidence, overtrading, tickeritis, hope, sentimentality, seeking pride and avoiding regret, self-control, wishful thinking, group think, herd instincts influencing the investor behavior. The researchers stated that the importance of the psychological factors cannot be underplayed as the understanding of the different market participant's psychology gives insight into trading patterns.

Tversky and Kahneman (1974), Slovic and Lichtenstein (1971) evaluated Human beings start evaluating final results by initiating from the beginning values about different situations. That starting point or beginning value may be the partial computation or the formulation of a problem. Adjustments are insufficient in both of the cases. Different initiating points come up with different estimates, which lead to initial values. This phenomenon is called 'anchoring'.

Agarwal (2012), Razek (2011), Hirshliefer and Luo (2011), Oberlechner and Osler (2009) De Bondt and Thaler (1995) defined overconfidence as an misinterpretation of the possibility for a set of events. The concept is significantly reflected by comparing whether the specific probability allocated is greater than the portion that is correct for all assessments allocated to the given probability. It causes people to overvalue their knowledge, undervalue risks and overvalue their ability to control events and the precision of their information. The author claimed that overconfidence originates in people's biased estimation of evidence. Many researchers find evidence for the presence

of the overconfidence bias in different financial decisions. Studies have shown that announcement returns are lower for overconfident bidders as compared to rational bidders. It is the outcome of the strongest identified by psychological research that is to say, investors tend to overvalue the probability of certainty of their information, their successes and capabilities'. They are having past positive outcomes and usually recall only their success than their failures. They find that there are two factors behind this behavior. These are: the underestimation of risk by the investors and overestimation of the success of their own trading program. Investors tend to be overconfident in two areas: they underestimate uncertainty and overestimate their own capabilities.

Kumar and Goyal (2014), Merli and Roger (2013) , Jaiswal and Kamil (2012), Olsen (2008) (Devenow & Welch, 1996), Scharfstein and Stein (1990) stated herding refers to the situation wherein coherent people start behaving illogically by copying the judgements of others while making decisions or it is the tendency of individual to chase the actions (rational or irrational) of a wider group or in other words it refers to the situation where forecasters or investors tend to shade their forecasts or investment decisions in the direction of a reference group (i.e., other market participants). It is the tendency of individuals to imitate the actions (rational or irrational) of a larger group; individually, however, most people would not necessarily make the same choice.

Rekik and Boujelbene (2013), Grinblalitt and Han (2004) explained the main idea underlying mental accounting is that decision-makers tend to divide the different types of gambles they face into separate accounts, and they apply prospect theoretic decision rules to each account by ignoring possible interplay between the accounts. Therefore, mental accounts can be divided not only with respect to time but also according to their subjects. It provides a foundation for the way that decision makers set referral points for the accounts that determine gains and losses.

Waweru et al. (2008), Barberis and Thaler, (2003), Ritter (2003), DeBondt and Thaler (1995), (Kahneman & Tversky, 1974) referred representativeness bias as the degree of resemblance that an event has with its parent population or the degree to which an event similitude to its population. It may result in some dispositions such as

people put too much importance on current experience and ignore the average long-term rate. A typical example for this bias is that investors often conclude a company's high long-term growth rate after some quarters of increasing. It also leads to the so-called "sample size neglect" which arises when people try to infer from too few samples. In stock market, when investors seek to buy "hot" stocks instead of poorly performed ones, this means that representativeness is there. This behavior is an explanation for investor overreaction.

Fogel and Berry (2006), Lehenkari and Perttunen (2004), (Shiller, 1998) asserted that investors consistently engage in behavior that they regret later. They avoid selling shares that have decreased in value, and readily sell shares that have increased in value. Psychologists have found that individuals who make decisions that turn out badly have more regret (blame themselves more) when the decision was more unconventional. For example buying a blue chip portfolio that turns down is not as painful as experiencing the same losses on unknown start-up firm. Any losses on a blue-chip stock can be more easily attributed to bad luck rather than bad decision making and cause less regret. Regret is an emotion occurs after people make mistakes. Investors avoid regret by refusing to sell decreasing shares and willing to sell increasing ones. Moreover, investors tend to be more regretful about holding losing stocks too long than selling winning ones too soon.

Lehenkari and Perttunen (2004), Barberis and Thaler (2003), Barberis and Huang (2001), Odean (1998a) referred Loss aversion as the different level of mental penalty people have from a similar size loss or gain. There is proof showing that people are more disappointed at the anticipation of losses than they are pleased by similar gains. Moreover, a loss coming after previous gain is proved less painful than usual while a loss arriving after a loss seems to be more painful than usual. They further found that both positive and negative returns in the past can raise the negative relationship between the selling trend and capital losses of investors, suggesting that investors are loss averse.

Limitations of the Study

- The researcher has taken her home state as an area for sampling that's why the conclusion drawn from this sample cannot be generalized on whole of India.

- Sample size is small and the researcher has taken her home state as area of research to make the data collection process easy and convenient.

Objectives

The primary objective of the study is to examine the influence of behavioral disposition on portfolio investment decisions of individual investors.

Hypothesis

H0: The various behavioral dispositions and their influence are not related with portfolio investment decisions of individual investors.

H1: The various behavioral dispositions and their influence are related with portfolio investment decisions of individual investors.

Methodology

It is a study which gives the influence of behavioral dispositions on portfolio investment decisions of individual investors. On the basis of the review of literature the following biases has been taken for the study viz. Herding bias, Overconfidence bias, Disposition bias, Mental Accounting bias, Anchoring bias, Representativeness bias, Loss Aversion bias and Regret aversion bias. The study undertakes five heuristic based biases and three prospect theory based biases. Expected Return, Amount of Investment, Time period of Investment has been taken as factors of Portfolio investment decisions.

The overall sample design is as follows:

Universe: Adults above 18 years of age.

Sampling Frame: List of investing clients from equity brokers in Rajasthan.

Sampling Unit: List of male and female investors in Rajasthan.

Sampling Technique: Non-Probability Convenience Sampling method.

Sample Size: 600 respondents.

Tools of Data Collection

The data for the present study has been collected through a structured questionnaire, questionnaire description. In order to study the investor's behavior, the researcher has used various behavioral finance variables. (Questionnaire statement reliability Cronbach's Alpha 0.856 for 64 items statements).

Data Analysis and Interpretation

For the purpose of the study Confirmatory Factor Analysis (CFA) and afterwards Structural Equation Modeling (SEM) has been used.

The CFA model is the focal point of the link between factors and their measured variables, within the framework of SEM, it represents what is called as a measurement model. In this study, the model was developed 'a priori', hence the CFA was used.

Structural equation modeling is exercised for examining the influence of exogenous constructs on investment decisions. It establishes path for concurrent testing of an entire model that covers multiple imaginary relationships. Structural equation model that consists of all constructs and hypothesized relations are examined.

Confirmatory Factor analysis was executed by using AMOS 24.0 software, it was calculated by using maximum likelihood among the variable via correlation. CFA was executed with the objective to define individual constructs and test whether the data fit a hypothesized measurement model. Validity and reliability of measurement model is evaluated.

To estimate model fit, some criteria such as the chi-square to degrees of freedom ratio (CMIN/df ratio), root mean squared residual (RMR), the comparative fit index (CFI), Parsimony adjusted mean and residual mean squared error of approximation (RMSEA) are determined. For CMIN/df value remain $<$ or $=$ 2 or 3. Values of CFI above 0.90 indicate good model fit. Parsimony closer to 1 is generally acceptable for good model fit. For RMSEA and RMR values below 0.05 indicate close fit, 0.08 indicate an adequate fit. Confirmatory factor analysis diagram is as follows:

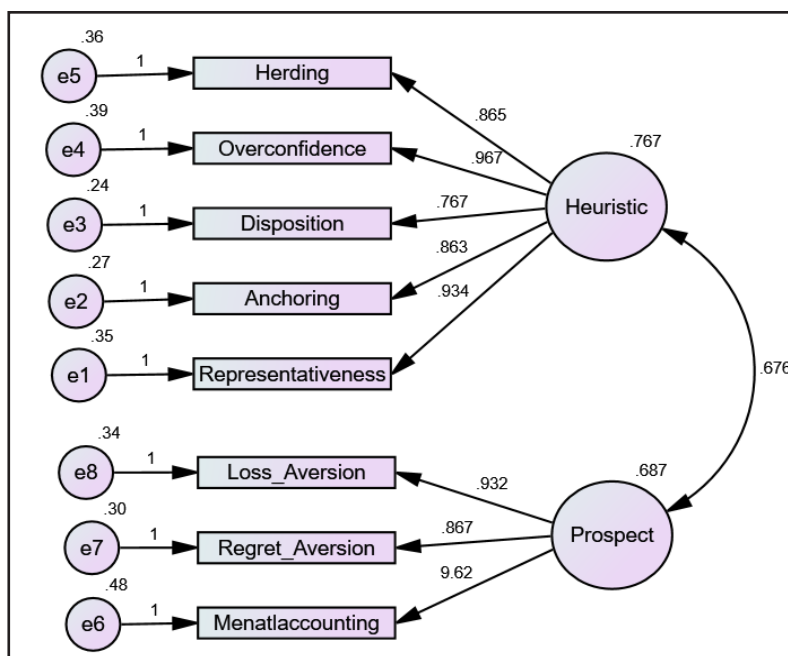


Fig. 1: Confirmatory Factor Analysis

The Measurement Model

Results for each construct are shown in Table 1. From 8 variable 2 latent variables are manifested named Heuristic: Herding (F1), Overconfidence (F2), Disposition (F3), Anchoring (F5) and Representativeness (F6), Prospect

includes Loss Aversion (F7), Regret Aversion (F8) and Mental accounting (F4). The CFA model fit the data well with CMIN/df is 2.31; GFI = 0.957; CFI = 0.956; RMSEA = 0.05 based on the statistics, the model fits the data very well, generating a good fit to the current data.

Table 1: Goodness of Fit Test

Latent Constructs and Variables	Factor Loadings	Composite Reliability	Average Variance Extracted
Heuristics			
Herding	0.865		
Over Confidence	0.967		
Disposition	0.767	0.767	0.71
Anchoring	0.863		
Representativeness	0.934		
Prospect			
Loss Aversion	0.932		
Regret Aversion	0.867	0.687	0.643
Mental Accounting	0.962		
Goodness-of-Fit	Statistics		
X2/DF (1to 4)		2.31	
GFI (> 0.90)		0.957	
AGFI (>0.80)		0.955	
CFI (>0.90)		0.956	

<i>Latent Constructs and Variables</i>	<i>Factor Loadings</i>	<i>Composite Reliability</i>	<i>Average Variance Extracted</i>
NFI (>0.90)		0.944	
RFI(>0.90)		0.924	
IFI(>0.90)		0.917	
TLI(>0.90)		0.939	
RMSEA(<0.08)		0.05	
RMR(<0.08)		0.025	

Source: Primary Data

It is apparent that in the above Table 1, latent construct take the factor loading which ranges from 0.863 to 0.962, indicating strong support for construct validity. Correspondingly, the average variance extracted values for heuristics and prospect theory are higher than the benchmark level of 0.50. Composite reliability coefficients are higher than 0.60 for both latent constructs, which shows that high internal reliability. Goodness of fit statistics of the measurement model further confirmed a good fit with the data. Various indexes are used here to measure the fit of the model including Goodness-of-Fit Index (GFI, 0.957); Adjusted Goodness-of-Fit Index (AGFI, 0.955); Normal-Fit Index (NFI, 0.944); Relative Fit Index (RFI, 0.924); Incremental Fit Index (IFI, 0.917); Tucker-Lewis Index (TLI, 0.939); and Root Mean Square Error of Approximation (RMSEA, 0.05) and (RMR.0.025) which are perfectly fit with the data.

Structural Equation Model

Structural Equation Model is a statistical technique for testing and approximating causal relations using a combination of statistical data and qualitative causal assumptions. This model is used to draw relationship between the variable. Model combines both the aspects factor analysis and multiple regression. This study profusely applied structural equation model and it is developed to test the influence of heuristic and prospect

biases on the investment decisions. Since, the proposed measurement model is in line with the data, the hypotheses are tested. Relationship among the constructs is showed in the Fig. 2. This study endeavored to test that there is a direct and positive relation between the biases and the investment decision

It is evident from the Fig. 2 below, among the different paths hypothesized in the model, all the paths are found significant at $p < 0.05$. This study tested the models illustrated in the above chart, which provide the path diagrams for the models on the defined investment decisions. Generally in Structural Equation Modelling the fit of the model is assessed by chi-square measure is not always straightforward. because chi-square is very sensitive to the sample size. Due to this disadvantage, various kinds of fit indexes have been developed that are independent sample size. The goodness of fit is presented in Table 2. To estimate model fit, some criteria such as the chi-square to degrees of freedom ratio (CMIN/df ratio), root mean squared residual (RMR), the comparative fit index (CFI), Parsimony adjusted mean and residual mean squared error of approximation (RMSEA) are determined. For CMIN/Df value remain $< \text{or} = 2 \text{ or } 3$. Values of CFI above 0.90 indicate good model fit. Parsimony closer to 1 is generally acceptable for good model fit. For RMSEA and RMR values below 0.05 indicate close fit, 0.08 indicate an adequate fit.

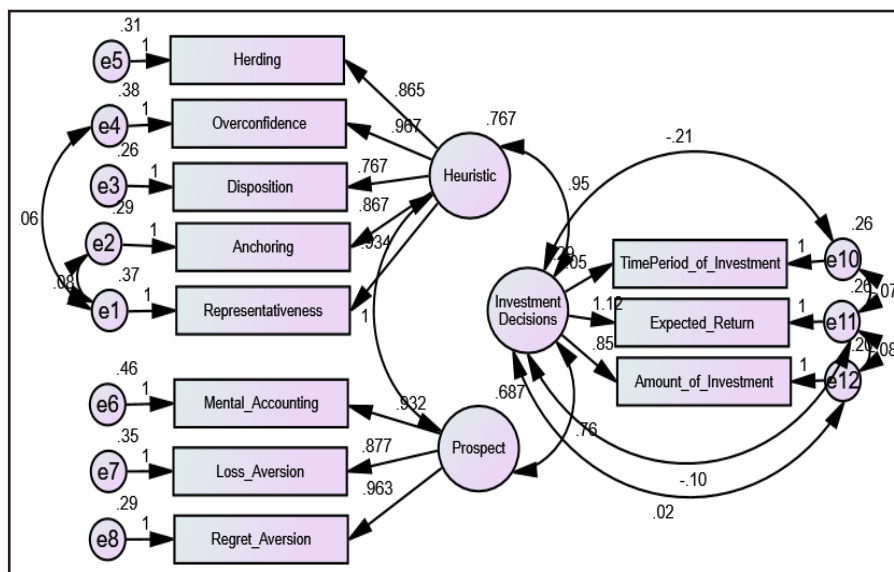


Fig. 2: Structural Equation Model

The Measurement Model

Results for each construct are shown in Table 2. From 8 variables 2 latent variables are manifested named Heuristic (F1, F2, F3, F5 and F6), Prospect (F7, F8 and

F4). The CFA model fit the data well with CMIN/ df is 2.14; GFI = 0.955; CFI = 0.966; RMSEA = 0.069 based on the statistics, the model fits the data very well, generating a good fit to the current data.

Table 2: Goodness of Fit Test

Latent Constructs and Variables	Factor Loadings	Composite Reliability	Average Variance Extracted
Heuristics			
Herding	0.865		
Over Confidence	0.967		
Disposition	0.767	0.767	0.73
Anchoring	0.867		
Representativeness	0.934		
Prospect			
Loss Aversion	0.877		
Regret Aversion	0.963	0.687	0.64
Mental Accounting	0.932		
Goodness-of-Fit	Statistics		
X2/DF (1to 4)		2.14	
GFI (> 0.90)		0.955	
AGFI (>0.80)		0.923	
CFI (>0.90)		0.966	
NFI (>0.90)		0.955	
RFI(>0.90)		0.936	
IFI(>0.90)		0.97	
TLI(>0.90)		0.952	
RMSEA(<0.08)		0.069	
RMR(<0.08)		0.034	

It is apparent that in the above Table 2, latent construct take the factor loading which ranges from 0.865 to 0.967, exhibiting strong support for construct validity. Correspondingly, the average variance extracted values for heuristics and prospect theory are higher than the benchmark level of 0.50. Composite reliability coefficients are higher than 0.60 for both latent constructs, which shows that high internal reliability. Goodness of fit statistics of the measurement model further confirmed a good fit with the data. Various indexes are used here to measure the fit of the model including Goodness-of-Fit Index (GFI, 0.955); Adjusted Goodness-of-Fit Index (AGFI, 0.923); Normal-Fit Index (NFI, 0.955); Relative Fit Index (RFI, 0.936); Incremental Fit Index (IFI, 0.97); Tucker-Lewis Index (TLI, 0.952); and Root Mean Square Error of Approximation (RMSEA, 0.069) and (RMR.0.034) which are perfectly fit with the data.

It is identified that this structural equation model accomplished significant improvement in terms of its goodness-of-fit indices as all recommended values are consistent. The result shows the data.

All these measures were found much better.

Conclusion

It can be concluded from the study that there exists a direct relationship between behavioral dispositions and portfolio investment decisions. It is inferred that both heuristic biases namely Herding, Overconfidence, Disposition, Anchoring, Representativeness and Prospect biases namely Loss aversion, Regret Aversion and Mental Accounting bias are considerably impact the portfolio investment decisions of individual investors.

The impact of the behavioral disposition on expected rate of return, amount of investment and time period of investment shows that the herd mentality, Overconfidence, Mental Accounting, Loss Aversion, Regret Aversion, Disposition, Representativeness, Anchoring all these biases have significant impact on portfolio investment decisions.

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