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Unveiling behavioural biases under the influence of socio-demographic variables: Evidence from equity investors in Southern Assam

Ms. Poonam Das*

Research Scholar, Assam University, Silchar, Department of Business Administration

Email: daspoonamaus@gmail.com

ORCID ID: 0009-0007-6842-7122

Dr. Amit Kumar Das

Associate Professor, Assam University, Silchar, Department of Business Administration

Email: amitdas.au@gmail.com

ORCID ID: 0000-0002-6497-9399

Abstract--With the consistent development of the financial market, equity investors' investment behaviour has undergone significant changes. The inconsistent practice of rationality by financial market participants causes the existence of market anomalies, leading to persistent deviations from rational pricing that are often unaddressed by the theories of "traditional finance". On the contrary, the theories of "behavioural finance" delineate how financial market participants systematically deviate from the rationality assumptions in the presence of behavioural biases, resulting in sub-optimal investment decisions. This study primarily explores the existence of behavioural biases among equity market participants in the Southern part of Assam. Based on the average value of the responses corresponding to each behavioural bias, the study finds the prominent presence of "anchoring bias", followed by "representativeness bias" and "disposition effect" among equity investors of the region. The statistical findings of the "independent sample t-test" and "one-way ANOVA", confirm a notable difference in "overconfidence bias", "anchoring bias", and "herding bias" due to differences in "gender", "education", "occupation", "annual income", and "investment experience" of the investors. With "multiple regression analysis," the study confirms that demographic variables of the investors

significantly affect behavioural biases, especially, a notable variation is observed in “overconfidence bias” due to the difference in demographic determinants of equity investors.

Keywords--Behavioural biases, Demographic variables, Equity investors, Financial market, Gender.
JEL classification: D91, G40, G41

1. Introduction

During the 1950s and 1960s, finance as a discipline witnessed a shift from descriptive discipline to a more scientific approach. Researchers across the globe focused more on the mathematical equations and probabilistic approach, which caused the development of finance theories such as “capital asset pricing model”, “efficient market hypothesis”, “portfolio optimization model”, etc (Andrikopoulos, 2005). These theories of traditional finance shared similar assumptions, such as investors’ rationality in decision making, risk aversion characteristics of investors, profit maximization objectives, and characteristics of security prices revealing all available information. However, the financial market has observed a distinct pattern of investment behaviour contradicting the presumptions of “traditional finance” theories. In “traditional finance”, the cornerstone theories such as “efficient market hypothesis” and “random walk model” suggest that at any time, security prices reflect the market available information, besides technical and fundamental analysis fail in predicting stock prices as they are unpredictable (Fama, 1970; Jensen & Benington, 1970). However, in a practical scenario, the presence of arbitrageurs in the financial market has questioned the validity of the assumptions of traditional finance theories. Empirical evidences have confirmed the presence of irrational investment behaviour among financial market participants with a systematic deviation from rationality when market prices of securities do not always reflect all the information. The existence of financial market anomalies, such as “calendar anomalies”, “momentum effect”, “disposition effect”, and “reversal effect”, supports consistent deviations from rational pricing. Such occurrences of market anomalies prompted researchers to assess the soundness and suitability of the assumptions of “traditional finance” theories.

This inability of “traditional finance” theories to explain such phenomena has marked the beginning of a new era known as “behavioural finance”, which has emerged from the critical discussion of traditional finance theories (Andrikopoulos, 2005). “Behavioural finance” attributes the irregularities in stock returns to different behavioural biases under the realm of human psychology (Barberis & Thaler, 2003). Researchers from this field argue that investors’ rational reactions in the financial market are often inconsistent. In uncertain situations, people often follow their instincts and intuitions while making investment decisions, going beyond the rationality assumption. Researchers from the field of psychology, Sociology, Economics, and Finance explain this deviation from rationality in the light of psychological determinants, which are considered as a framework for interpreting investors’ behaviour through input, representation, processing, and output (Pompian, 2006). In behavioural finance, these psychological factors are known as “behavioural bias” (Kapoor & Prosad,

2017; Smith, 2008), which disrupts the rational process of assessing financial information and encourages investors to take investment decisions based on psychological factors, irrational preferences, instincts, and intuitions (Kartini & Nadha, 2021). Hence, behavioural finance aims to offer insights into market anomalies related to investors' investment behaviour stimulated by "cognitive" and "emotional" biases. "Cognitive biases" are often considered as the misinterpretation of available information such as "availability bias", "overconfidence bias," "representativeness bias", "anchoring bias", "cognitive dissonance bias", "self attribution bias", "mental accounting bias", "confirmation bias", "hindsight bias", "recency bias", "framing bias", etc. On the other hand, "emotional biases" are traced to illogical reasoning such as "endowment bias", "self-control bias", "optimism bias", "loss aversion bias", "regret aversion bias", "status quo bias", etc. In the presence of these biases, investors investment behaviour is found to contradict the rationality assumption of decision-making (Pompian, 2006). Empirical evidences support that behavioural biases not only influence investment decisions of the investors but also have a significant effect on investment attitude and the level of risk tolerance (Singh, 2019). With the rapidly growing world economy, market participants are exposed to a variety of investment avenues. Thus, the changing financial market, along with the identification of behavioural biases at the individual level of investors, demands more advanced investment strategies. To attain optimal investment decisions, analyzing the influence of behavioural biases along with investors' demographic characteristics is considered vital for financial market participants. This study aims to offer a comprehensive understanding of behavioural finance by unveiling behavioural biases in relation to the socio-demographic variables of equity investors in the Southern part of Assam. The subsequent sections of the study highlight the conceptual structure and recent developments of "behavioural finance" and investors' behaviour in decision making respectively, followed by the objectives of the study, research methodology, data analyses, key findings, discussion and conclusion, implications of the findings for both industry and academia, limitations and future scope of the study.

2. Review of theoretical and empirical literature

2.1 Theoretical framework of "Behavioural Finance"

The theories of traditional finance are based on the premise that investors in the financial market behave rationally in the landscape of available information in security prices (Ricciardi, 2008). The "expected utility theory" described the utility function based on a mathematical model, which raised questions of its applicability for investors making decisions under uncertainty and risk. Similarly, the rationale behind the concept of "capital asset pricing model" (CAPM) had been criticized on the grounds of its risk-return relationship. Empirical evidence confirmed the influence of different price ratios in explaining average return provided by beta value (Fama & French, 2004). With CAPM, the security prices were determined based on the element of systematic risk; while in a complex scenario, a single-factor model is insufficient to explain security prices. Existing literature supported that the skewness of the stock returns distribution was a better measurement of risk as beta values for individual stocks change over time (Ricciardi, 2008). Another cornerstone theory introduced by Eugene Fama in "traditional finance" was the "efficient market hypothesis" (EMH). The theory was

based on the fundamental assumptions of market efficiency, where security prices were assumed to reveal available information of the financial market (Fama, 1970). However, existing literature has documented that security prices exhibit volatility more than the efficient market could explain (Shiller, 2003). Such inability of traditional finance theories in explaining financial market phenomena has encouraged researchers to think beyond mathematical models of investment strategies. Gradually, researchers from the field of psychology and economics came together to explain the stock market anomalies from psychological perspectives (Singh, 2019). This development marked the beginning of “behavioural finance” as a distinct paradigm in the field of Finance (Kapoor & Prosad, 2017). “Behavioural finance” aims to address unexplained market anomalies by incorporating the psychological perspectives of stock market investors. The path-breaking research in “behavioural finance”, is the introduction of “prospect theory,” which replaced the utility functions of “expected utility theory” (Kahneman & Tversky, 1979). According to “expected utility theory”, investors are considered to maximize their expected utility. However, “prospect theory” underpinned the cognitive assessment of outcomes based on a point of reference instead of absolute values. The theory explains the risk-averse characteristics of investors in a situation of potential losses, while they become risk-takers with potential gains. Kahneman and Tversky (1979) suggested that investors in the financial market deviate from rationality in a non-random manner by following a non-uniform risk attitude, focusing on a psychological anchor, and assigning greater emphasis on losses than on equivalent gains. Such irrational behaviour of investors leads to mispriced securities and a stock market bubble. Bondt and Thaler (1985, 1987) discovered that market participants are inclined to react to dissimilar events, which was further conceptualized as “market over-reaction and under-reaction”. Bondt and Thaler (1985) proposed the concept of “mental accounting” by differentiating individuals’ propensity to isolate information into different mental accounts. Shefrin and Statman (2000) argued that investors in the financial market are often optimistic by prioritizing more of the positive aspects of a past event and neglecting the other side of the same event. People in uncertain situations follow heuristics to interpret information in a quick manner based on their past experiences and intuitions (Kartini & Nadha, 2021). The use of heuristics leads to quick decision-making, often triggered by behavioural biases such as “representativeness bias”, “anchoring bias”, and “availability bias”. Thus, the foundation of behavioural finance lies in the scientific study of cognition that influences human behaviour. The core principle of behavioural finance lies in understanding investors’ psychology to elucidate deviations observed in the financial market (Singh, 2019). The holistic term of such psychological aspects is known as behavioural biases, which cause systematic errors in judgment (Pompian, 2006). The presence of such behavioural biases not only influences investment decisions but often leads to an adverse impact on the portfolio performance (Fischer & Gerhardt, 2007).

2.2 Behavioural biases and investment decisions

An increasing number of research works have evidenced the significant impact of irrational trading activities on the financial market. Aggressive investment strategies often lead to price variation of stocks at the macro level (Kaniel et al., 2008). In the presence of an inaccurate pattern of price movements, many investors follow herd behaviour to estimate the patterns of price movements in

the financial market (Bondt & Thaler, 1987). M. Baker and Wurgler (2007) discovered that the investors' sentiment in the stock market profoundly impacts the efficiency of decision-making. Kartini and Nadha (2021) documented that investors deviate from the rationality assumption of the financial market in the light of psychological biases. Such biases hinder the process of assessing available information, resulting in following certain beliefs and intuitions (Zindel et al., 2014). As compared to investors' personality traits, such heuristics substantially influence the investment decisions (Atif Sattar et al., 2020). Another study conducted on the participants of the "Pakistan Stock Exchange" supported that market participants were inclined to hold the losing stocks by selling the winners (Ahmed et al., 2022). Moreover, Indonesian investors' investment decisions were observed to be affected by certain behavioural biases, such as "anchoring bias", "representativeness bias", "overconfidence bias", "optimism bias", "herding bias", and "loss aversion bias" (Kartini & Nadha, 2021). Similarly, "overconfidence bias", "anchoring bias", and "herd behaviour" of Pakistani investors considerably influence their investment decisions. However, financial literacy level plays an effective role as a moderator in the association of "overconfidence bias" and investment decisions of the investors (Mahmood et al., 2024). Gentile et al. (2015) focused on the relationship between risk perception and information presentation, highlighting the influence of framing bias on investment decisions. The study concluded that the investors often ignore investment opportunities based on their cognitive complexity in understanding financial information, instead of a logical interpretation of the associated risk related to the investment. Similarly, when investment opportunities are attractively framed, investment decisions become significantly dependent on psychological biases (Hidajat et al., 2020). Suchanek (2021) identified that, apart from the Behavioural biases, investors' personality traits also play a significant role in shaping the investment decision Behaviour. The study connected the characteristics of dark personality with overconfidence and herding biases and concluded that personality traits of the investors intensify biased investment behaviour. Lebdaoui et al. (2021), and Salman et al. (2021) focussed on the level of financial literacy of the stock market participants by analysing its moderating role on the association of Behavioural biases and investment decisions. The study concluded that, with a higher level of financial literacy, the influence of overconfidence bias can be reduced to a certain extent. However, financial literacy level can strengthen the association of representativeness bias and investment decision, indicating a non-linear relationship between financial knowledge and behaviour.

2.3 Behavioural biases and demographic variables

The steps involved in decision-making are considered rational when they are backed up by a logical flow of thinking to attain an optimal outcome. Mintzberg et al. (1976) proposed three distinct stages of the rational decision-making process, which starts with problem identification, followed by searching for suitable alternatives for problem solving, and finally selecting the best alternative to attain the desired outcome. However, findings of the existing literature have confirmed that the steps involved in rational decision-making are substantially influenced by psychological errors and socioeconomic status of the investors (Coskun et al., 2016; Prosad et al., 2015; Tekce & Yilmaz, 2015). A study conducted on mutual fund investors confirmed the impact of "gender", "educational qualification", and

“investment experience” on overconfidence and self- attribution bias (Mishra & Metilda, 2015). In terms of gender, male investors exhibit a higher tendency towards overconfidence bias as compared to female investors (H. K. Baker et al., 2019; Tekce & Yilmaz, 2015). Similarly, H. K. Baker et al. (2019) found that overconfidence bias stems from investment experience, while age and occupation significantly influence behavioural biases and investment decisions. Abreu (2019) confirmed that behavioural biases significantly differ between stock market investors and those investing in warrants. Younger investors are found to be more inclined towards investment in warrants. Research evidence across the globe has confirmed that investors’ participation in the stock market is increasing. However, with the changing pattern of the financial market, the investment strategy of the market participants is not consistent. Consequently, it constitutes a challenge to the financial service providers to accurately assess the investment attributes of the investors. Although researchers across the globe have documented micro and macro level factors influencing investment decisions. However, an increasing trend of scholarly attention to investors’ behaviour under the realm of psychology has been observed in developed nations, while comparatively fewer studies have been conducted in geographically diverse and less-studied areas, especially in the North-Eastern region of India. The Southern part of Assam, in the North-Eastern region of India, is exceptional in terms of its diversified socio-economic status and cultural differences among people (Dey & Haloi, 2019; Islam, 2025), which may result in a differentiated behaviour of investment among individual investors. The statistical data published by the “Bombay Stock Exchange” (BSE) shows a year-wise increasing pattern of investor count in the state of Assam. However, the data is available only at the state level, and no district-wise data or regional data is found. As a result, research work in the “behavioural finance” field, relating to investment decisions is limited within its sub-region, especially the Southern part of Assam, consisting of Cachar, Karimganj, Hailakandi, and Dima Hasao districts. Such insufficient scholarly attention creates a significant research gap to check whether the growing pattern of investors in the entire state is uniformly reflected in the Southern part of Assam, or it brings a unique trend of investment behaviour among the individual investors in comparison to the other parts of the state. Thus, the present study aims to address this research gap by focusing on the investment patterns of equity investors in the Southern part of Assam. The study primarily aims to identify the presence of behavioural biases in the investment decisions of individual investors in the region. Further, the relationship between demographic variables of the investors with identified behavioural biases has been established with suitable statistical analyses. Finally, the study concludes by offering insights for financial advisors, policy makers, and financial market participants.

3. Objectives of the study

- To explore the presence of behavioural biases among individual equity investors in the Southern part of Assam
- To evaluate the role of socio-demographic attributes on behavioural biases among individual equity investors in the Southern part of Assam

4. Research Methodology

The core objective of the study is based on the causal relationship between demographic variables and behavioural biases of individual equity investors. Hence, the nature of the present study is explanatory and empirical. The selection of the behavioural biases in the present study is based on the empirical evidence supporting their significant presence among investors' investment behaviour documented in the previous literature. The study aims to analyse the presence of five behavioural biases among individual equity investors in the Southern part of Assam, which consists of "overconfidence bias", "herding bias", "representativeness bias", "anchoring bias" and "disposition effect". The total number of individual equity investors from the six active and functional financial brokerage houses registered within a time period from 18th April 2025 to 11th May 2025, of Cachar, Karimganj, Hailakandi, and Dima Hasao districts of the Southern part of Assam formed the population of the study. By using Cochran's formula on the total number of registered individual equity investors of the identified brokerage houses within the selected time frame, a sample size of 367 has been determined for the study. The study follows a cross-sectional method for data collection, and responses were collected through simple random sampling by distributing a "five-point Likert scale" questionnaire to the six brokerage houses of the region based on the proportionate ratio of registered equity investors at each brokerage houses. The researcher personally distributed the questionnaire to the individual equity investors visiting the branch during on-site visits to the selected brokerage firms, under the surveillance of the branch manager. The questionnaire ranges from "strongly disagree" = 1, "disagree" = 2, "neutral" = 3, "agree" = 4, and "strongly agree" = 5. The questionnaire is divided into two parts; part "A" consists of seven factors of socio-demographic profile of the respondents, such as "gender", "age", "marital status", "educational qualification", "occupation", "annual income", and "investment experience". Part "B" consists of components related to five behavioural biases such as "overconfidence bias", "herding bias", "representativeness bias", "anchoring bias" and "disposition effect". The sources of the variables used in the study are presented in Table 1. A total number of 358 complete responses is found adequate for subsequent analysis of the study. Responses collected from the sample size have been further analyzed by "Statistical Package for Social Sciences" (SPSS, version 21). The study initially scrutinises and validates the collected responses with the help of visual screening, "skewness and kurtosis" analysis (Hair, 2010), "Exploratory Factor Analysis" (Hair, 2010), "Cronbach Alpha" analysis (Hair, 2010; Hair et al., 2019; Nunnally, 1975; Prosad et al., 2015), analysis of normality of the standardised residuals (Barker & Shaw, 2015), "multicollinearity" analysis (Hair, 2010), and examining the homoscedasticity of the regression models (Field et al., 2012). The study identifies the presence of selected behavioural biases based on the composite score of the respondents corresponding to each behavioural bias (Mishra & Metilda, 2015; Prosad et al., 2015). With the help of "independent sample t-test" and "one-way ANOVA", the study determines the variation among identified behavioural biases across different demographic variables of the respondents. The study further employs "multiple regression analysis" to examine the influence of demographic variables of equity investors on the identified behavioural biases (H. K. Baker et al., 2019; Coskun et al., 2016; Mishra & Metilda, 2015). The study has used "Large Language Model" (LLM) for refining

text, enhancing the quality and accuracy of the research work by critical examination and validation to ensure relevance and adherence to academic standards.

Table 1: Sources of the variables under study

Variables of the study	No of items	Source
Demographic variables	7	(Baker, Kumar, Goyal, & Gaur, 2019)(Prosad, Kapoor, & Sengupta, 2015)(Mishra & Metilda, 2015; Sahi et al., 2013)
“Overconfidence bias”	9	(Prosad, Kapoor, & Sengupta, 2015)(Metawa et al., 2019)(Abideen et al., 2023)(Mushinada & Veluri, 2019)(Baker, Kumar, Goyal, & Gaur, 2019)(CAO et al., 2021)
“Herding Bias”	5	(Baker, Kumar, Goyal, & Gaur, 2019)(CAO et al., 2021)(Ahmed et al., 2022)(Abideen et al., 2023)(Metawa et al., 2019) (Prosad, Kapoor, & Sengupta, 2015)(Lin, 2011)
“Representativeness Bias”	6	(Baker, Kumar, Goyal, & Gaur, 2019)(Rasheed et al., 2018)(CAO et al., 2021)(Ogunlusi & Obademi, 2021)
“Anchoring Bias”	4	(Baker, Kumar, Goyal, & Gaur, 2019)(CAO et al., 2021)(Ogunlusi & Obademi, 2021)
“Disposition Effect”	5	(Prosad, Kapoor, & Sengupta, 2015)(Ahmed et al., 2022)(Abideen et al., 2023)(Baker, Kumar, Goyal, & Gaur, 2019)

Note: The table: 1 represents the literature sources of the variables employed in the study consisting of “demographic variables”, “overconfidence bias”, “Herding bias”, “Representativeness bias”, “Anchoring bias”, and “Disposition effect”.

Source: Author’s own compilation based on existing literature review

5. Data analysis and findings

A visual scrutiny was conducted to eliminate the incomplete responses before conducting the statistical analysis. The presence of missing responses and outliers has been examined to maintain the accuracy of the collected data. Further, no outlier was found during the scrutiny, leading to a total sample size of 358 respondents.

5.1 Normality of individual variables

Initially, the assumption of normality of the study variables has been verified with the “skewness” and “kurtosis” values. The values of “skewness” and “kurtosis” presented in Table 2 fulfil the assumption of normality as all the variables fall within the acceptable range of “skewness” and “kurtosis,” i.e., “+1 to -1” and “+3 to -3” respectively (Hair, 2010).

Table 2: Normality Statistics of individual variables

Variables	N	Mean	Standard d.	Skewness	Kurtosis
“Overconfidence Bias”	358	3.1527	1.05343	.261	-.801
“Herd Behaviour”	358	3.1682	.99781	.126	-.829
“Anchoring Bias”	358	3.2800	.84679	-.451	-.147
“Representativeness bias”	358	3.2845	.78967	-.620	.105
“Disposition effect”	358	3.2330	.85558	-.140	-.437

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

5.2 Factor analysis

An Exploratory Factor Analysis (EFA) is employed to check the structure of the measurement items with respect to their underlying variables (Hair et al., 2019). “Principal Component Analysis” and “varimax” rotation have been used for the extraction method. The study has found that communalities for all the dimensions of the study are within the acceptable range, i.e., above .50 (Hair, 2010). The sample adequacy is measured with “Kaiser-Meyer-Olkin” in Table 3, which confirms the data suitability for factor analysis (0.879). Further, the “Bartlett’s Test of Sphericity” has verified the significance of correlation among variables, where “Chi-square” ($n = 358$) = 5634.780 ($p < 0.001$). Table 4 shows that the analysis has yielded five factors for the scale, which explain 54.458 percent of the total variance in the data. Table 5 represents the summary of the factor analysis with five constructs identified as a result of EFA. Factor 1 refers to “overconfidence bias” (OC) that includes items from OC1 to OC9. Factor 2 refers to “herding bias” (HER) that includes items from HER1 to HER5. Factor 3 refers to “representativeness bias” (REP) that includes items from REP1 to REP6. Factor 4 refers to the “disposition effect” (DIS) that includes items from DIS1 to DIS5. Factor 5 refers to “anchoring bias” (ANC) that includes items from ANC1 to ANC4.

Table 3: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.879
Approx. Chi-Square	5634.780
Bartlett's Test of Sphericity	
df	465
Sig.	.000

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

Table 4: Total Variance Explained

Factor	Eigenvalue	% Variance Explained	Cumulative %
Factor 1	6.513	21.011	21.011
Factor 2	3.499	11.287	32.298
Factor 3	2.367	7.635	39.932
Factor 4	2.269	7.320	47.252

Factor	Eigenvalue	% Variance Explained	Cumulative %
Factor 5	2.234	7.206	54.458

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

Table 5: Rotated Component Matrix

Items	1	2	3	4	5
OC1	.785				
OC2	.800				
OC3	.836				
OC4	.809				
OC5	.791				
OC6	.791				
OC7	.867				
OC8	.829				
OC9	.774				
HER1		.769			
HER2		.823			
HER3		.786			
HER4		.811			
HER5		.689			
REP1			.567		
REP2			.509		
REP3			.520		
REP4			.716		
REP5			.645		
REP6			.704		
DIS1				.556	
DIS2				.494	
DIS3				.517	
DIS4				.712	
DIS5				.784	
ANC1					.644
ANC2					.518
ANC3					.693
ANC4					.664

Note: This table represents the factor loadings of five behavioural biases through “Principal Component Analysis” with “Varimax” rotation, where, OC: “overconfidence bias”, HER: “herding bias”, REP: “representativeness bias”, ANC: “anchoring bias”, DIS: “disposition effect”

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

5.3 Reliability of the Instrument

The internal consistency of the studied variables has been tested with “Cronbach’s Alpha” analysis. A variable is considered reliable based on the numeric value of Alpha (α) above 0.70 (Hair, 2010; Hair et al., 2019; Nunnally,

1975; Prossad et al., 2015). The test results in Table 6 confirm the presence of reliability for all the constructs of the study (Alpha (α) > 0.70).

Table 6: Reliability Statistics

	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
“Overconfidence bias”	.941	.941	9
“Herding”	.857	.857	5
“Representativeness”	.772	.772	6
“Anchoring”	.711	.711	4
“Disposition effect”	.729	.726	5

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

5.4 Normality of standardized residuals

The study has further tested the normality of regression residuals, confirming the assumption of OLS regression relates to the distribution of error terms (Barker & Shaw, 2015). The “P-P Plots” of standardised residuals (Appendix figure 1 to figure 5) of the dependent variables such as “overconfidence bias”, “herding bias”, “representativeness bias”, “anchoring bias”, “disposition effect” demonstrate that the residuals are close to the reference line with minor deviations observed for the dependent variable of “representativeness” bias, indicating the residuals are approximately normally distributed.

5.5 Multicollinearity test of explanatory variables

The demographic variables of the study, i.e. “gender”, “age”, “marital status”, “educational qualification”, “occupation”, “annual income”, and “investment experience” have been converted into dummy variables for the purpose of regression analysis. The collinearity among the explanatory variables is checked with the help of “tolerance” and “Variance Inflation Factor” (VIF) (Hair, 2010). The results, as shown in Table 7, indicate that the “tolerance” values for all the demographic variables are above the minimum threshold value i.e. 0.10 and the VIF values are found below 5 indicating no multicollinearity is found among demographic variables of the investors. However, the VIF values of investors above the age group of 60 and investors with post-graduate qualification report 6.054 and 5.042, respectively, indicate no serious multicollinearity issue.

Table 7: Multicollinearity Statistics

Model	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
Gender “female”	.627	1.596
Age “30 to less than 45”	.277	3.604
Age “45 to less than 60”	.245	4.083
Age “60 above”	.165	6.054
Marital status “unmarried”	.559	1.790

Model	Collinearity Statistics	
	Tolerance	VIF
Marital status "widowed"	.747	1.338
Education "graduate"	.241	4.153
Education "post-graduate"	.198	5.042
Education "doctorate"	.390	2.564
Education "any other"	.935	1.070
Occupation "private sector employee"	.484	2.068
Occupation "public sector"	.473	2.116
Occupation "student"	.385	2.596
Occupation "retired"	.214	4.674
Occupation "any other"	.622	1.606
Annual income "3 to less than 6 lakh"	.227	4.411
Annual income "6 to 10 lakh"	.211	4.731
Annual income "10 lakh and above"	.290	3.450
Investment experience "1 year to less than 5 years"	.411	2.435
Investment experience "5 to less than 10 years"	.341	2.930
Investment experience "10 years and above"	.451	2.216

Note: This table represents the value of multicollinearity statistics through "tolerance" and "variance Inflation Factor" (VIF).

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

5.6 Test of Homoscedasticity

The assumption of homoscedasticity is tested before conducting "multiple regression analysis" to ensure the constant variance of the residuals across all the levels of independent variables (Field et al., 2012). The scatter plot analysis (Appendix figure 6 to figure 10) for standardised residuals report two data points for "representativeness bias" fall on the extreme right, all other residuals corresponding to "overconfidence bias", "herding bias", "anchoring bias", and "disposition effect" are within the acceptable range and their variance is found to be approximately constant, indicating an absence of heteroscedasticity.

6. Socio-demographic profile of the respondents

Table 8 represents the demographic distribution of the equity market participants of the Southern part of Assam. Table 8 also represents the frequency value and the corresponding percentage of each demographic variable of 358 individual equity investors. The "descriptive statistics" of "gender" reveal that 233 (65.1%) respondents of the collected responses constitute male investors, and 125 investors are female, indicating 34.9% of the entire sample. This finding highlights the disparity and dominance of male investors in investment decisions. The "age" statistics reveal that the majority of the respondents (n=172, 48%) fall in the "30 to less than 45" age group, followed by 24% respondents belonging to the "45 to less than 60" age group. With respect to "marital status", 61.7% of the

total respondents are married. Further, a noticeable number of respondents are graduates (n = 151, 42.2%), where a total of 146 respondents reported having a “post-graduate” degree. Respondents working in the “private sector” constitute 28.2% of the entire sample size, and 175 number of total respondents report their annual income ranges between “3 to less than 6 Lakh” (48.9%). Finally, 39.9% respondents (n = 143) have an investment experience of “1 to less than 5” years. Only 7.3% respondents (n = 26) have investment experience above 10 years.

Table 8: Demographic profile of the individual equity investors

Profile	Group	Frequency	Percentage
“Gender”	Male	233	65.1
	Female	125	34.9
	Total	358	100
“Age”	18 to less than 30	71	19.8
	30 to less than 45	172	48.0
	45 to less than 60	86	24.0
	60 and above	29	8.1
“Marital status”	Total	358	100
	Married	221	61.7
	Unmarried	127	35.5
	Widowed	10	2.8
“Education”	Total	358	100
	Undergraduate	33	9.2
	Graduate	151	42.2
	Post Graduate	146	40.8
	Doctorate	27	7.5
	Any other	1	0.3
“Occupation”	Total	358	100
	Business/Self Employed	71	19.8
	Private Sector Employee	101	28.2
	Public Sector Employee	96	26.8
	Student	44	12.3
	Retired	22	6.1
	Any other	24	6.7
	Total	358	100

Profile	Group	Frequency	Percentage
"Annual income"	Less than 3 Lakhs		
	3 to less than 6 Lakhs	70	19.6
	6 to less than 10 Lakhs	175	48.9
	10 Lakhs and above	29	23.5
	Total	358	8.1
"Investment experience in stock market"	Less than 1 years		
	1 to less than 5 years	105	29.3
	5 to less than 10 Years	143	39.9
	10 years and above	26	23.5
	Total	358	7.3

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

7. Equity investors and behavioural biases

The study commences with the identification of behavioural biases among individual equity investors in the Southern part of Assam. The average score of the respondents corresponding to each behavioural bias is reported. The composite average score of each behavioural bias above 3 indicates the presence of that behavioural bias among 358 respondents of the study (H. K. Baker et al., 2019; Mishra & Metilda, 2015; Prosad et al., 2015). Ranks of the behavioural biases are also given based on their average value, indicating their prominent presence among the investors of the study. Table 9 exhibits the presence of all five behavioural biases under study among individual equity investors. Based on the ranks of these behavioural biases, "anchoring bias" is the most prominent bias, followed by "representativeness bias", "disposition effect", "herding bias", and "overconfidence bias".

Table 9: Ranking of behavioural biases

Biases	N	Mean	Rank
"Anchoring Bias"	358	3.29	1
"Representativeness bias"	358	3.28	2
"Disposition effect"	358	3.23	3
"Herding bias"	358	3.17	4
"Overconfidence bias"	358	3.15	5

Note: This table represents the ranking of the selected behavioural biases based on their mean values among 358 respondents.

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

8. Demographic variables and behavioural biases of individual equity investors

To determine the differences in behavioural biases due to different demographic variables under study, statistical tools like “independent sample t-test” and “one-way ANOVA” have been deployed (H. K. Baker et al., 2019; Coskun et al., 2016; Mishra & Metilda, 2015; Sahi et al., 2013). “Independent sample t-test” evaluates the varied presence of behavioural biases due to differences in the “gender” of the respondents. Similarly, the “one-way ANOVA” test has been employed to assess the variation in behavioural biases across “age”, “education”, “occupation”, “annual income”, and “investment experience” of the investors. The result of the “independent sample t-test” (Table 10) reveals a significant variation in the presence of “overconfidence bias” between male and female respondents. The mean difference, as shown in Table 10, supports the significant presence of overconfidence bias among male respondents than female investors. On the contrary, a significant variation in herding bias across gender reveals that female investors’ inclination towards herd behaviour is more than that of male respondents. The result exhibits no significant variation in “Representativeness bias”, “Anchoring bias”, and “Disposition effect” across male and female respondents of the study. Further, the results of “one way ANOVA” as shown in Table 11, represent the differences in behavioural biases across demographic variables, such as “age”, “marital status”, “education”, “occupation”, “annual income”, “investment experience” among 358 respondents. The results of “ANOVA” indicate that the presence of “overconfidence bias” varies across different levels of “age” group and “marital status” of the investors. There is a significant variation observed in the presence of “overconfidence bias”, “herding bias”, and “anchoring bias” with different levels of “educational qualification”, “occupation”, “annual income” and “investment experience” of the investors. However, no significant variation is observed in “representativeness bias” and “disposition effect” in respect to the demographic variables of the respondents.

Table 10: Behavioural biases across gender

	Levene's Test for Equality of Variances				t-test for Equality of Means				
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
“Overconfidence bias”	19.215	.000	7.316	317.521	.000	.74132	.10133	.54196	.94068
“Herding bias”	8.550	.004	-5.445	222.798	.000	-.60452	.11103	-.82331	-.38572
“Representativeness bias”	.319	.573	-.460	356	.646	-.04028	.08765	-.21265	.13209
“Anchoring bias”	2.237	.136	1.707	356	.089	.15984	.09363	-.02430	.34398
“Disposition effect”	.177	.674	-1.125	356	.261	-.10669	.09482	-.29317	.07979

Note: This table represents the significance value of “Levene’s test”, “t-value”, Significance value of “independent sample t-test” and “mean difference” of behavioural biases across gender among 358 respondents.

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

Table 11: Behavioural biases and demographic variables

Variables	Age		Marital status		Education	
	F	P Value	F	P Value	F	P Value
“Overconfidence bias”	2.376	.070	3.697	.026	15.192	.000
“Herding bias”	3.463	.017	1.835	.161	2.761	.028
“Representativeness bias”	.401	.753	1.293	.276	2.090	.082
“Anchoring bias”	.418	.740	.106	.899	6.655	.000
“Disposition effect”	1.409	.240	2.818	.061	.895	.467
Occupation		Annual Income		Investment experience		
Variables	F	P Value	F	P Value	F	P Value
“Overconfidence bias”	5.198	.000	18.728	.000	31.332	.000
“Herding bias”	2.618	.024	7.391	.000	14.175	.000
“Representativeness bias”	.731	.601	1.115	.343	2.232	.084
“Anchoring bias”	3.936	.002	6.119	.000	6.985	.000
“Disposition effect”	.458	.808	1.609	.187	.641	.589

Note: This table represents the value of “mean square”, “F” and Significance value of “one way ANOVA” of behavioural biases across “age”, “marital status”, “education”, “occupation”, “annual income”, “investment experience” among 358 respondents.

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

9. Influence of demographic variables on behavioural biases of individual equity investors

To assess the influence of demographic variables on selected behavioural biases of individual equity investors in the Southern part of Assam, “multiple regression analysis” is performed where behavioural biases are measured on a continuous scale, and demographic variables are measured on a categorical scale (H. K. Baker et al., 2019). Table 12 summarizes the empirical results of “multiple regression analysis” for five regression models, where “gender”, “age”, “marital status”, “education”, “occupation”, “annual income”, and “investment experience” form independent variables, and behavioural biases such as “overconfidence bias”, “herding bias”, “representativeness bias”, “anchoring bias”, and “disposition effect” are considered as dependent variables. The β coefficient represents the numerical effect of each demographic variable against the reference category of behavioural biases. For “gender”, male investors are considered as the reference category. Investors from the age group of “18 to less than 30” form the reference category for “age” group. For “marital status”, married investors form the reference category. Similarly, investors having educational qualification of “undergraduate”, occupation as “business/self employed”, annual income as “less than 3 lakh” and investment experience ‘less than 1 year” form the reference category for “educational qualification”, “occupation”, “annual income”, and “investment experience” respectively. Further, the study has used a weighted sum

score for the regression analysis. The five models of regression equation with respect to behavioural biases and investment decisions are shown in the following:

Model I:

Overconfidence bias = $\beta_0 + \beta_1(\text{Gender}) + \beta_2(\text{Marital status}) + \beta_3(\text{Age}) + \beta_4(\text{Educational qualification}) + \beta_5(\text{Occupation}) + \beta_6(\text{Annual income}) + \beta_7(\text{Investment experience}) + e_i$

Model II:

Herding bias = $\beta_0 + \beta_1(\text{Gender}) + \beta_2(\text{Marital status}) + \beta_3(\text{Age}) + \beta_4(\text{Educational qualification}) + \beta_5(\text{Occupation}) + \beta_6(\text{Annual income}) + \beta_7(\text{Investment experience}) + e_i$

Model III:

Representativeness bias = $\beta_0 + \beta_1(\text{Gender}) + \beta_2(\text{Marital status}) + \beta_3(\text{Age}) + \beta_4(\text{Educational qualification}) + \beta_5(\text{Occupation}) + \beta_6(\text{Annual income}) + \beta_7(\text{Investment experience}) + e_i$

Model IV:

Anchoring bias = $\beta_0 + \beta_1(\text{Gender}) + \beta_2(\text{Marital status}) + \beta_3(\text{Age}) + \beta_4(\text{Educational qualification}) + \beta_5(\text{Occupation}) + \beta_6(\text{Annual income}) + \beta_7(\text{Investment experience}) + e_i$

Model V:

Disposition bias = $\beta_0 + \beta_1(\text{Gender}) + \beta_2(\text{Marital status}) + \beta_3(\text{Age}) + \beta_4(\text{Educational qualification}) + \beta_5(\text{Occupation}) + \beta_6(\text{Annual income}) + \beta_7(\text{Investment experience}) + e_i$

Where,

β_0 = Intercept

β_1 = Coefficient for "gender"

β_2 = Coefficient for "marital status"

β_3 = Coefficient for "age"

β_4 = Coefficient for "education"

β_6 = Coefficient for "annual income"

β_7 = Coefficient for "investment experience"

e_i = Error term

Model I: Demographic variables and "overconfidence bias"

The explanatory power (R²) of Model I is 31.3 percent. Table 12 demonstrates that "gender", "age", "marital status", "education", "occupation", and "investment experience" are statistically significant with respect to "overconfidence bias". However, females are found to be less overconfident than males (beta = -0.337 and P = .008). Equity investors' of "45 to less than 60" age group are less overconfident than those from the age group of "18 to less than 30". Similarly, unmarried equity investors are less overconfident than married investors. Contrary to this, investors falling under the group of "any other" academic qualification possess higher overconfidence than "undergraduate" equity investors. Equity investors who belong to "student" category are found more overconfident than "business/self employed" investors. The findings also conclude that equity investors with a higher level of investment experience are more overconfident than those with less than one year of experience.

Model II: Demographic variables and “herding bias”

The explanatory power (R2) of Model II is 14.3 percent. Table 12 shows that "gender" and "investment experience" are statistically significant in relation to "herding bias". Female investors ($\beta = 0.304$ and $p = 0.023$) are found to have more "herding bias" as compared to male equity investors. On the other hand, equity investors with "investment experience" of "1 to less than 5 years" and "5 to less than 10 years" have less "herding bias" as compared to investors with "investment experience" of "less than one year". The findings suggest that investors are less susceptible to "herding bias" when they possess more "investment experience".

Model III: Demographic variables and “representativeness bias”

The explanatory power (R²) of Model III is 6.60 percent. Table 12 shows that “occupation” is statistically significant in relation to “representativeness bias”. It is found that “representativeness bias” among retired equity investors is less than that of the investors from the “business/self-employed” category. However, demographic variables such as “gender”, “age”, “education”, “marital status”, “annual income”, and “investment experience” are found to be insignificant in predicting the response variable.

Model IV: Demographic variables and “anchoring bias”

The explanatory power (R²) of Model IV is 12.2 percent. Table 12 shows that “education” and “investment experience” are statistically significant in relation to “anchoring bias”. The study concludes that “post-graduate” equity investors exhibit a greater inclination towards “anchoring bias” than “undergraduate” investors. Similarly, investors with “1 to less than 5 years” of “investment experience” have greater anchoring bias than investors with “less than 1 year” of experience.

Model V: Demographic variables and “disposition effect”

The explanatory power (R2) of model V is 7.4 percent. Table 12 shows that "age", "marital status", and "annual income" are statistically significant in the "disposition effect". The result has demonstrated that equity investors from the age group of "45 to less than 60 years" have low "disposition effect" as compared to investors from the "18 to less than 30 years" age group. On the other hand, investors who belong to the "widowed" category have a higher level of "disposition effect" than that of "married" investors. Similarly, investors with an "annual income" of "10 lakh and above" have a higher level of "disposition effect" than those with an "annual income" of "less than 3 lakh".

Table 12: Regression analysis of demographic variables on behavioural biases

experience (Less than 1 year = 0)										
1 year to less than 5 years	.485	.00	-	.01	.178	.180	.26	.04	-	.99
		1	.41	0			2	0	.00	7
			4						1	
5 to less than 10 years	.827	.00	-	.01	.042	.803	.28	.10	-	.47
		0	.49	6			6	3	.13	1
			0						1	
10 years and above	.693	.01	-	.09	.138	.563	.11	.63	-	.62
		2	.48	4			8	3	.12	7
			5						5	
R ²	0.313		0.143		0.066		0.122		0.074	
F	7.298		2.671		1.135		2.221		1.271	

Note: n = 358. This table presents the results of linear regression on behavioural biases across and demographic variables of equity investors. The table represents significance value at the 0.05 level or higher. β : unstandardized coefficient; p: significance value; independent variable: "gender", "age", "marital status", "education", "occupation", "annual income" and "investment experience". Dependent variable: "overconfidence bias", "herding bias", "representativeness bias", "anchoring bias", "disposition effect".

Source: Compiled on the basis of results obtained from the analysis of data through SPSS

10. Discussion and conclusion

The core objective of the study lies in the identification of behavioural biases among individual equity investors in the Southern part of Assam. In reference to the numerical average of the factors corresponding to each behavioural bias, the findings of the study confirm the existence of "overconfidence bias", "herding bias", "representativeness bias", "anchoring bias", and "disposition effect" among individual equity investors. This finding confirms the similar observations reported in previous research H. K. Baker et al. (2019), Mishra and Metilda (2015), Prosad et al. (2015, 2018), Sahi et al. (2013), and Sharma and Firoz (2020). Among all the identified behavioural biases, "anchoring bias" is the most prevalent behavioural bias among individual equity investors, followed by "representativeness bias" and "disposition effect". This brings light to the behavioural inclination of investors towards initial information related to investment. However, investors also make investments influenced by "anchoring bias" by depending on the stock buying prices and trend analysis of the representative stocks. Further, the observed disposition effect also indicates investors' characteristics of holding the losing stocks while selling the winners. The study further investigates the variation among behavioural biases due to demographic characteristics of the investors. Findings from the "independent sample t-test" indicate statistically significant variation across gender, which confirms the previous findings of H. K. Baker et al. (2019), Prosad et al. (2015), and Tekce and Yilmaz (2015). However, female investors follow herd behaviour more than male investors. The findings from "one-way ANOVA" reveal that different levels of "educational qualification", "occupation", "annual income", and "investment experience" of the investor cause a significant variation among "overconfidence bias", "anchoring bias", and "herding bias". Moreover, overconfidence bias and disposition effect vary significantly among investors in different age groups. Similarly, investors from the "retired" category have

significantly different levels of “representativeness bias” than investors from the “business / self-employed” category. Finally, overconfidence bias among equity investors varies significantly with each level of investment experience. The result exhibits that higher levels of investment experience are associated with overconfidence bias as compared to lower levels of experience, confirming the findings of Prosad et al. (2015). Findings from the empirical analyses confirm that the socio-demographic distribution of the respondents causes a variation among behavioural biases. Additionally, results of the “multiple regression analysis” report that demographic characteristics of the investors cause 31.3% variation in overconfidence bias. The findings of the present study align with the previous evidence reported by H. K. Baker et al. (2019), Kalra Sahi and Pratap Arora (2012), Mishra and Metilda (2015), Mushinada and Veluri (2019), Prosad et al. (2015, 2018), Sahi et al. (2013), and Sharma and Firoz (2020). The statistical findings support that individual equity investors of the Southern part of Assam are inclined towards several behavioural biases that influence their investment behaviour, leading to suboptimal decisions. The study has been conducted in the underexplored region of Assam, India, where an accurate estimation of the investment psychology of equity investors is challenging due to its non-uniform patterns of demographic and cultural structure. In the presence of behavioural biases, investors in uncertain situations are observed to follow heuristics and deviate from the concept of rationality. The presence of such biases among investors’ decision-making is inherent; however, steps can be taken to alleviate the impact of psychological biases on investment decisions by increasing the level of financial literacy of market participants. Based on the findings reported by Abideen et al. (2023), Anwar et al. (2023), H. K. Baker et al. (2019), Kasoga (2021), and Khan (2020), financially literate investors are expected to follow rational behaviour in decision-making by mitigating the impact of psychological biases on decision-making to a certain extent. Calvet et al. (2009), Lusardi and Mitchell (2014), and Van Rooij et al. (2011) reported that a higher level of financial literacy among investors can accurately extract and process the available market information to achieve efficient investment decisions.

11. Implications for Industry, Regulators and Policy Makers

The study findings provide meaningful insights for financial institutions, stock market intermediaries, policy makers, financial advisors, and financial market participants working in the Southern part of Assam. The presence of behavioural biases indicates that equity investors of the studied region are predominantly influenced by their intuitive judgments instead of rationally assessing available market information. This finding highlights the need for financial industries to strengthen advisory services for the market participants, and offer investment avenues that limit the influence of recurring behavioural errors. Financial brokerage houses can create more accurate investor profiling and design customized advisory recommendations by considering the risk tolerance abilities of the respondents. Additionally, policymakers and financial market regulators may conduct different workshops and seminars to enhance the understanding of areas such as the financial market, investors’ psychology in decision making, and awareness of behavioural biases among investors. They can also offer tailored initiatives to increase the level of financial literacy based on the disparities observed in behavioural biases due to different demographic attributes of the

investors. Targeted awareness interventions can be organized for the male investors who show a higher inclination towards overconfidence bias. Similarly, investors who show higher susceptibility towards herd behaviour may also be addressed by different financial literacy programs to enhance their understanding of the effect of behavioural biases on investment decisions. Regulators of the financial market may also ensure that the available financial information is easily accessible and understandable by the investors, leading to a decreasing dependency on heuristics such as “representativeness bias” and “anchoring bias”. Monitoring disclosure requirements and offering investor-friendly financial information can contribute to reducing behavioural errors and possible market anomalies while decision making. Overall, the study findings encourage a coordinated initiative by financial institutions, stock market intermediaries, policy makers, financial advisors, and financial market participants to offer a more robust, better-informed, and behaviourally sensitive investment environment for the investors.

12. Limitations and future scope of the study

This study considers a few limitations that are to be recognized. The population of the present study was limited to individual equity investors of the Southern part of Assam; however, individual investors of the other part of the state might bring light to a completely different pattern of investment behaviour. The sample size of the study, though diverse, failed to represent all categories of investors present in the geographical area of the study and focused only on the equity market participants. Moreover, a cross-sectional research design has been adopted with selected behavioural biases, which limits the scope of understanding the changing patterns of investment behaviour over a period of time, as well as the impact of other behavioural biases on investment decisions of the investors. Future research scope may focus on investors from other parts of the state or may focus on national and international financial markets, offering a cross-regional comparison. Adopting a longitudinal research design with a larger variety of psychological biases can give a holistic understanding of the changing trend of investment behaviour over a long period of time. Additionally, future studies may integrate the performances of digital platforms and AI-powered advisory tools with investment psychology to offer a distinct insight into the factors influencing investment decisions.

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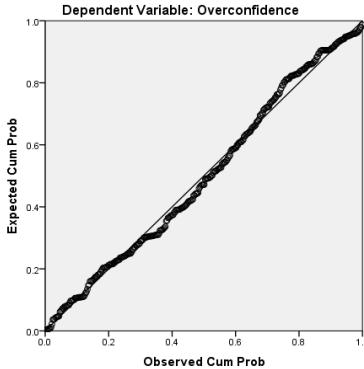
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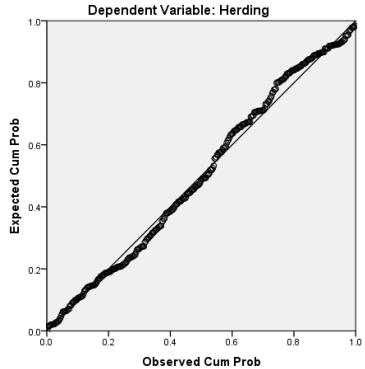
Appendix

A. Normality of standardized residuals

Normal P-P Plot of Regression Standardized Residual



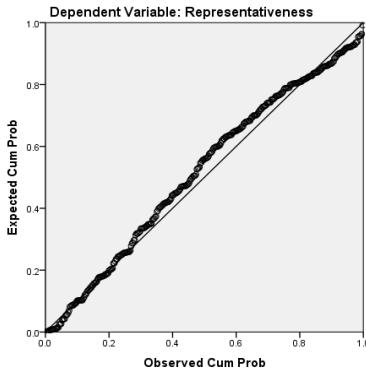
Normal P-P Plot of Regression Standardized Residual



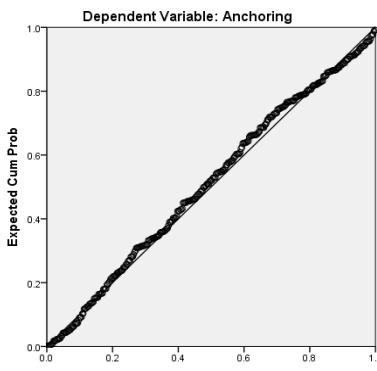
*Figure 1 Normal P-P plot of regression standard residual
plot of regression standard residual*

Figure 2 Normal P-P

Normal P-P Plot of Regression Standardized Residual



Normal P-P Plot of Regression Standardized Residual



*Figure 3 Normal P-P plot of regression standard residual
plot of regression standard residual*

Figure 4 Normal P-P

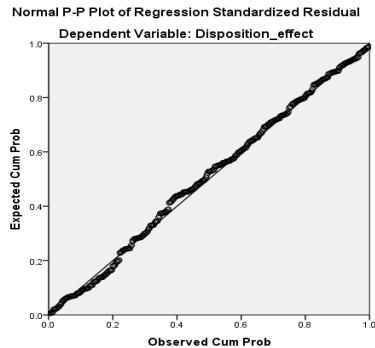


Figure 1 Normal P-P plot of regression standard residual

B. Test of Homoscedasticity

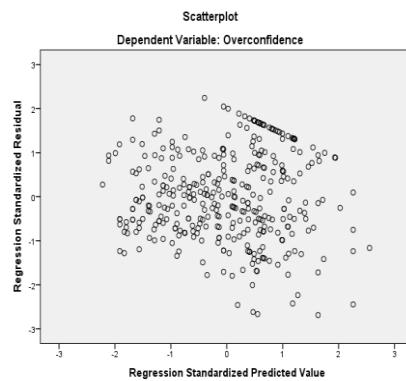


Figure 6 Scatter plot of standardized residuals against standardized predicted values for the “overconfidence bias” regression model I

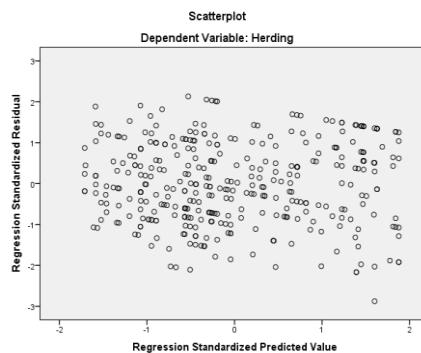


Figure 7 Scatter plot of standardized residuals against standardized predicted values for the “herding bias” regression model II

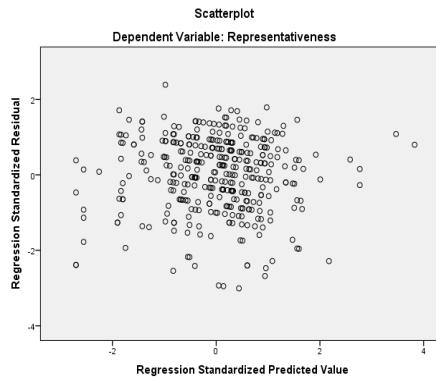


Figure 8 Scatter plot of standardized residuals against standardized predicted values for the “representativeness bias” regression model III

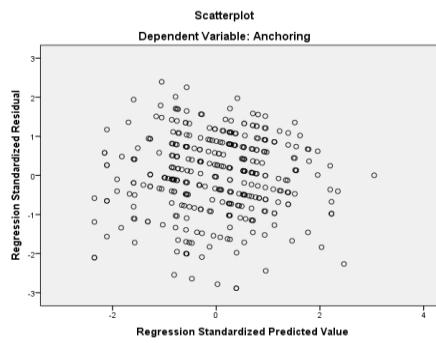


Figure 9 Scatter plot of standardized residuals against standardized predicted values for the “anchoring bias” regression model IV

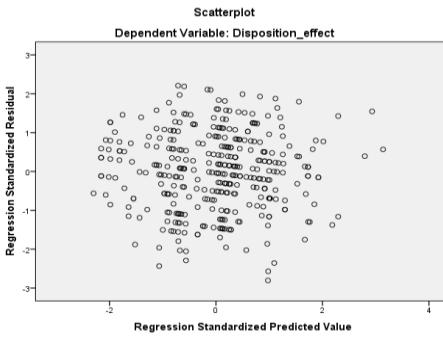


Figure 10 Scatter plot of standardized residuals against standardized predicted values for the “disposition effect” regression model V