THE IMPACT OF GENERAL ELECTIONS IN INDIA ON STOCK MARKETS AND INVESTORS' BEHAVIOURAL BIASES IN THE MEDIUM AND SHORT-TERM

by

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DEDICATION

I dedicate this research to the esteemed late Dr. Daniel Kahneman, a pioneering figure in behavioural finance. He is a Nobel Prize laureate for integrating psychological research insights into economic science, especially concerning human judgment and decision-making under uncertainty. At the time of the award in 2002, he was affiliated with Princeton University, Princeton, NJ, USA. He was born on 5 March 1934, in Tel Aviv, British Mandate of Palestine (now Israel). He passed away on 27 March 2024.

His influential work on Prospect Theory, along with Amos Tversky, critically examines how individuals often deviate from rational decision-making processes. They published a series of articles introducing new theories and concepts that helped the field of behavioural finance to evolve as a new discipline of finance. Some of their ideas and their prominent articles that inspired me to delve further into behavioural finance are:

- "Availability: A Heuristic for Judging Frequency and Probability," (Tversky & Kahneman, 1973a)
- "Judgement Under Uncertainty: Heuristics and Biases,"(Tversky & Kahneman, 1974)
- "Prospect Theory: An Analysis of Decision Under Risk,"(Kahneman & Tversky, 1979)
- "Rational Choice and the Framing of Decisions," (Tversky & Kahneman, 1986)
- "Advances in Prospect Theory: Cumulative," (Tversky & Kahneman, 1992)
- "Maps of Bounded Rationality": Physiology of Behavioural Economics (*Bounded Rationality_Kahnem 2003*, n.d.)

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ABSTRACT

THE IMPACT OF GENERAL ELECTIONS IN INDIA ON STOCK MARKETS AND INVESTORS' BEHAVIOURAL BIASES IN THE MEDIUM AND SHORT-TERM

Preliminary observations from historical data of the Indian stock market during the five Indian General Elections (GEs)—specifically in 2004, 2009, 2014, 2019, and 2024—reveal predictable and anomalous market behaviour patterns.

Firstly, an examination of medium-term performance revealed that the total stock market returns, as reflected by the NIFTY50 Total Return Index (NIFTRI), experienced an impressive average growth of 35.1% across the five election years. When considering individual election years, the returns ranged from 14.16% to 77.8% annually. The substantial average growth notably exceeds the historical long-term average annual return of 14.92% observed during non-election years from 2000 to 2024.

Secondly, evidence from market data of a shorter timeframe—approximately one month surrounding the announcement of GE results—revealed that the India VIX, which measures market volatility, demonstrated unusually heightened volatility compared to non-election periods over the 16-year period from 2008 to 2024.

These findings suggest a departure from the principles outlined in the Efficient Market Hypothesis (EMH), a cornerstone of traditional finance. According to the EMH, investors are presumed to be rational actors who instantly incorporate all pertinent information into stock prices, rendering the market unpredictable. Conversely, this study posits that investor behaviour during GEs is markedly influenced by psychological factors distinct in “Behavioural Finance” theories. Such biases undermine intrinsic market valuations, leading to discrepancies between investor preferences and probabilities derived from classical financial theories.

Appropriate statistical tests conducted with the empirical data presented herein established that significant differences in returns and volatility exist within the Indian stock markets during Indian GEs, as opposed to other periods. Furthermore, the survey methodology employed in this research confirmed the prevalence of significant cognitive and emotional biases among investors. This elucidation provides insight into the underlying financial biases that contribute to predictable price movements and heightened volatility in the market during times of economic uncertainty.

The study emphasises that investors and policymakers must acknowledge these biases and adopt informed investment strategies during uncertain times to mitigate potential losses. Ultimately, it makes a substantial contribution to the field of “Behavioural Finance,” reinforcing its principles and expanding its theoretical frameworks across diverse contexts, conditions, and timeframes.

Keywords: *Indian General Elections, Stock Market Volatility and Returns, Efficient Market Hypothesis, Behavioural Finance, Cognitive and Emotional Biases.*

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CHAPTER I:

INTRODUCTION

1.1 Introduction

Classical financial experts endeavour to apply rational financial models, such as the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH), to evaluate stock markets by incorporating all available information that impacts future company cash flows. However, human beings are not entirely rational; they inherently possess biases that form a natural part of decision-making. These financial biases can lead to diverse assumptions regarding the future economic landscape. Such departures from rationality often result in predictable and abnormal market outcomes, particularly during political uncertainty, as seen in the Indian general elections.

Stock prices are inherently forward-looking, reflecting expectations regarding a company's future earnings. Consequently, the stock market is a leading indicator of the nation's economic outlook. "A causal relationship exists between the stock market and the economy" (Causality et al., 1996). In classical finance, stocks are valued based on the anticipated future cash flows of the companies, with the assumption that investors price in all the information rationally and instantaneously. However, these assumptions do generally not align with the prescribed rational process. Instead, the valuations are influenced by investors' various behavioural biases.

Fiscal policies play a crucial role in shaping a nation's business environment, serving as a roadmap for government expenditures and taxation that influences economic dynamics. These policies are contingent upon the size of the economy (Easterly & Rebelo+, 1993). Consequently, the financial repercussions of such policies can be particularly pronounced in large and developing economies like India, which, as of the end of 2023, is estimated to have a GDP of USD 3.57 trillion (source: www.tradingeconomics.com/india/gdp), ranking it fifth globally.

In India, the government formulates fiscal policies. Political parties assume governance as a single largest entity or through coalitions with other parties to secure a majority mandate from the electorate during GEs, which are conducted every five years. These elections involve various qualified political parties, each representing distinct ideologies on reforms and policies that impact social, cultural, legal, administrative, environmental, and economic development. Thus, GEs extend beyond political events; they represent critical economic milestones. Therefore, the results of these elections can have substantial implications for the future business landscape, influencing policy decisions, regulatory environments, and overall financial stability. The intersection of electoral outcomes and economic conditions warrants careful examination with rational minds, as these elections can reshape the dynamics of industries and markets on national and global scales.

1.2 Research Problem

Political uncertainty during GEs in India introduces significant unpredictability regarding the new Government and its policies, potentially altering the country's economic future. In such uncertain times, as per classical finance theories and models, investors are theoretically expected to adopt a rational and unbiased approach to pricing the stocks, based on all available information and best estimates of intrinsic values.

Theories in classical finance, often referred to as neoclassical, standard or traditional finance, are fundamentally grounded in “Modern Porfolio Theory” (MPT), CAPM and EMH. MPT was formulated by Harry Markowitz in 1952 and examines a portfolio's expected return, standard deviation, and the correlations among various assets to construct an efficient portfolio. It assumes that investors are risk-averse and their financial preferences are to maximise their returns with minimum risk. William Sharpe followed up on the theory with CAPM in 1964, which predicts the relationship between risk and returns of an asset and an efficient portfolio. This model is based on one of the many assumptions that investors have homogeneous expectations and they constantly endeavour to maximise their utilitarian benefits. Eugene Fama formulated the theory of EMH in 1964, asserting that the current market price corresponds to its fair value. Consequently, proponents of the EMH argue that active traders and portfolio managers cannot consistently achieve superior returns that exceed market performance over time, due to the unpredictable nature of the market.

However, empirical data from the Indian stock market prices reveal an abnormal and predictable pattern during the Indian GEs. This abnormal pattern suggests a logical association with investors' financial decision errors, reinforcing behavioural financial theories that propose a shift towards alternative financial models, such as Behavioural Asset Pricing Model (BAPM) and Behavioural Portfolio Theory (BPT), which incorporate investors' biases in asset and portfolio pricing.

“A purely rational approach is being subsumed by a broader approach based on the psychology of investors” (Hirshleifer, 2001a). His statement challenges the basic foundations of classical finance, whose roots are in the EMH (Fama, 1970), which assumes that the investors in the capital markets act rationally and that:

• Current stock prices incorporate all available information and expectations.

• Current stock prices are the best approximation of intrinsic value.

• Price changes are unpredictable and often occur due to unforeseen events.

• “Mispricing” does occur, but not in predictable patterns that can lead to consistent outperformance.

The emergence of behavioural finance (BF) over the past few decades has consistently reinforced many of its hypotheses and theories about how investors struggle to make rational investment decisions in uncertain situations due to the heuristics and biases inherent in human decision-making.

Renowned neuroscientist Andrew Lo presents the “Adaptive Market Hypothesis” (AMH) as an alternative to the EMH. The AMH encompasses several key concepts:

- Individuals exhibit unique behaviours and are prone to errors.
- Competition drives both adaptation and innovation.
- Natural selection influences market dynamics and evolution

(Lo, n.d.)

1.3 Purpose of Research

Examining the empirical evidence of mispricing in the Indian stock markets during GEs from 2000 to 2024 necessitates comprehensive testing and analysis of the research hypotheses. This investigation is pivotal to reinforcing the general understanding in BF that uncertainties in situations contribute to short-term heightened biases in investors, leading to financial errors in their decisions. Such biases may stem from the psychology of fear, hope, self-control, anger, disgust, surprise, regret, contentment, and shame, among others. Conversely, as the uncertainties of the situations subside in the medium term, stock markets typically yield returns in alignment with the economy's fundamental factors. This effect can be attributed to the mood of the investors, which has milder yet longer-lasting effects than emotion in the investors (Chandra, 2020). The current study aims to assess abnormal market volatility over thirty days (short-term) and abnormal market returns for a longer period of one year (mid-term) surrounding the Indian GEs from 2000 to 2024.

“It is impossible to make complex tools without understanding cause and effect” (Wolpert, 2003). He highlighted the significance of understanding “cause-and-effect” relationships in human evolution. To elucidate the factors contributing to the observed stock market phenomena during Indian GEs, a series of statistical tests were conducted involving stock market participants to establish a cause-and-effect relationship between human biases and the predictability of mispricing in the stock market.

1.4 Significance of the Study

This study significantly enriches our understanding of investor behaviour by revealing how psychological factors can distort decision-making, particularly in volatile market environments. It highlights that cognitive and emotional biases exacerbate market fluctuations, particularly during critical periods such as elections or periods of political turmoil. The importance of this research lies in its ability to pinpoint specific scenarios where financial misjudgments are most likely to occur, thus fostering a heightened awareness of the emotional and cognitive biases that influence investor actions. Moreover, the findings of this study can empower investors to identify and confront or accept their own biases. This self-awareness is crucial in promoting more disciplined and informed investment strategies, allowing investors to make decisions based on adaptive rather than purely rational methods. By cultivating a deeper understanding of these psychological factors, investors are better equipped to navigate turbulent markets, which can ultimately lead to improved financial outcomes over time.

In addition to its implications for individual investors, this research holds broader significance for policymakers and regulators. It can inform the creation of comprehensive, adaptive strategies to mitigate the negative consequences associated with the limitations of a purely rational approach. By gaining insights into how political uncertainty influences investor sentiment, regulators are better equipped to design educational programs that foster an adaptive decision-making process. Such initiatives can enhance not just market stability but also investors' satisfaction by equipping investors with the tools they need to respond thoughtfully to shifting market conditions.

Ultimately, this study serves as a vital resource for both theoretical knowledge and practical applications, enhancing the integrity of financial markets. Addressing the psychological dimensions of investing not only aids individual investors but also contributes to a more resilient and stable financial ecosystem.

1.5 Research Questions

Two key research questions that this study aims to address are:

1. Do the Indian stock markets diverge from their intrinsic pricing, as outlined by classical financial theories, during periods of political uncertainty, such as during GEs in India?

2. Do investors exhibit financial biases in their decision-making processes, leading to mispricing in the stock market?

CHAPTER II:

REVIEW OF LITERATURE

2.1 Theoretical Framework

The literature review establishes a significant connection among key relevant themes of the research topic, establishing an association between the stock markets, economic performance, fiscal policies, government ideologies, general elections, and investors' behavioural biases. It explains the financial implications of human biases within the stock markets during the Indian GEs, culminating in the central topic of the research: “The Impact of General Elections in India on Stock Markets and Investors' Behavioural Biases in the Short and Medium Term.”

2.1.1 Stock Markets and the Economy

Stock Markets are good indicators to measure a country's economic performance (Causality et al., 1996). They concluded that the results of their project reveal that the stock markets help predict the country's future economy. Although economic fluctuations may occur before they are reflected in stock prices, changes in stock prices typically indicate shifts in a country's gross domestic product (GDP). This is an important finding, as it provides additional support for the notion that stock markets signal an economic shift in advance. Theoretically, stock prices predict economic activity due to traditional valuation models of stock prices. These models incorporate parameters that reflect performance expectations for the future economy (Chuang & Wang, 2009).

Fluctuations in stock prices directly impact aggregate spending. Investors feel wealthier and spend more when the stock market rises, leading to economic expansion. Conversely, investors feel less wealthy when stock prices decline and reduce spending, resulting in slower economic growth (Pearce & Roley, 1984). The authors found that stock prices typically begin to fall six months to a year before a recession starts and tend to rise again around the midpoint of the economic contraction, before the beginning of an economic recovery. The "wealth effect" suggests that stock prices influence economic activity by actively shaping the economy . Their idea supports the theory that stock markets can predict the economy, reinforcing the findings of several other researchers who have shown that stock markets are leading indicators of the country’s future economic performance.

2.1.2 Economy and the Government

Political events have a significant impact on the economic policies of developing countries. Empirically and theoretically, they concluded that elections in developing countries have had a positive impact on their economic governance and policies. Elections discipline governments to perform well (Chauvet & Collier IRD, 2008). According to their findings, after 1990, elected governments were compelled to adopt good policies by the electorate.

Among all economic policies, fiscal policies are the most crucial for creating a healthy business environment that fosters a country's long-term development and sustainable growth (Easterly & Rebelo+, 1993). They emphasised the relationships among fiscal policy variables, development levels, and growth rates in the following points:

- There is a strong association between a country's level of development and its fiscal structure: poorer countries tend to rely heavily on international trade taxes. In contrast, income taxes play a more significant role in developed economies.

- The scale of the economy, as measured by its population, influences fiscal policy.

- The effects of taxation are challenging to isolate empirically.

Theoretically, fiscal policy can stimulate growth, depending on its tax structure and government expenditure. Using a panel data set for 22 OECD countries from 1970 to 1995, with a 5-year average and accounting for any implicit financing assumptions associated with the government budget constraint (Kneller et al., 1999). They found that :

- Distortionary taxation reduces growth, whilst non-distortionary taxation does not.

- Productive government expenditure enhances growth, whilst non-productive expenditure does not.

Economic policies, particularly fiscal policies announced by a government, may have a short-term or long-term impact on the country's financial and business environment, and are likely to be reflected in its stock markets. The research was conducted on a significant economic event, the surprise announcement of demonetisation in India, which significantly impacted the chosen stock market indices- Sensex, NIFTY, and BSE100 (Sathyanarayana & Gargesha, 2017).

The Impact of Political Events on Pakistan's Stock Market. Karachi Stock Exchange-100 index returns over fifty major political events were selected from 1998 to 2013. Negative abnormal returns were observed before and after the event for a few days (Mahmood et al., 2014). The study verified a significant relationship between political events and stock market returns.

Companies reduce their capital investments by an average of 4.8% during election years compared to non-election years (Julio & Yook, 2012). They found evidence to support their hypothesis that firms reduce and stall further business investments during political and electoral uncertainty. They also observed how governments shape policy to stimulate investment in the short term and formulate regulatory and economic policies in the long term. They concluded that further investment planning depends on the newly elected government, as it has implications for industry and trade regulations, as well as fiscal and monetary policies. Elections with closely contested results lead to deeper investment cycles than those where the victor wins by a large margin. They also found that investment rates drop more in election years in which the incumbent national leader is classified as "market-friendly" by the World Bank. The ruling party's ideologies, which form the government, significantly affect how the country's future economic growth will develop during its governance.

In a democratically elected government, the voters decide on the changes they expect to see through their elected candidates and parties. Voters evaluate the past economic performances of the competing political parties and vote for the party that provides the highest "expected future utility". The US Presidential election results from 1976 to 1996 supported the view that voters look only at the economic performance of the current party in power. They do not also look at the performance of the opposition party the last time it was in power. Furthermore, the voters assessed the growth rate of actual per capita output in the current election year, suggesting that they look back only about one year of work (Fair, 1996).

2.1.3 General Elections and the Stock Markets

General election results increase the stock market volatility mainly due to uncertainty about the outcome of the results. In a sample including 27 OECD countries, the country-specific market index return variance can be twice as much during the week around an election day due to various reasons, including narrow margin of victory, loosely defined voting laws, change in the political ideologies of the new government, and unstable form of coalition government (Piotr, n.d.).

An academic paper, "Investment Returns under Right—and Left-Wing Governments in Australia" (Anderson et al., n.d.), considered the link between ruling political parties and stock, property, and bond returns in Australasia. The authors observed that left-leaning governments had higher inflation, which resulted in higher property returns during labour terms. Stock markets did better when right-leaning governments had lower inflation.

After more than 60 years of Barisan Nasional governance in Malaysia, it lost to Pakatan Harapan. The results of the 14th general election shocked the Malaysian financial market. Results from the statistical analysis revealed significant changes in the Malaysia stock market performance after the 14th general election (Misman et al., 2020).

A study on the 2013 Zimbabwe Presidential Elections suggested strong evidence of abnormal returns before and after the elections. However, low-volume margins were traded on days nearer to the result day. Cumulative abnormal returns were meager, too. For periods before the election results date, cumulative returns were minimal. These could be due to the uncertainty of Presidential results as high cumulative abnormal returns were seen after the election results (Murekachiro, 2014).

A study examining the relationship between national electoral events and stock market returns in various presidential elections in Nigeria found evidence that the banking and petroleum sectors experienced decreases before and increases after the elections. Conglomerate stock prices oscillated in the same direction in 1999 and 2003 (Eboigbe & Modugu, 2018).

The uncertainty surrounding a nation's economic environment extends beyond the announcement of election results and persists until the newly elected government articulates its policy priorities (Oehler et al., n.d.). They found that the elections of recent U.S. presidents have yielded abnormal returns for companies and sectors, regardless of the political affiliations of the elected officials. Their analysis yields two primary conclusions: first, the market remains in a state of uncertainty and does not adjust until the political priorities of the president are clearly defined; second, the market encounters difficulties in reconciling the implications of political shifts, thereby raising questions about the efficiency of the market in response to political influences. There seem to be some behavioural effects concerning the market efficiency and slowness of the market reaction. However, ultimately, the market corrects and thus reflects changes in the underlying governing ideologies. Despite some identifiable distinctions between the political profiles of the Republican and Democratic parties, changes in stock returns appeared to be driven by market expectations related to individual presidents rather than any differences in the political decision-making between the parties.

A research paper, “The effect of General Election on the stock market performance of firms: Evidence from India” (Garg et al., n.d.), establishes a positive and statistically significant effect of Indian GEs on the stock market performance of all the firms in India. A similar estimation from the random effect model also presented evidence supporting the positive effect of the general election on the firms' performance.

“Investors can earn abnormal returns by systematically investing during political uncertainty.” (Savita & Ramesh, 2015). Their report stated that national general elections are important political events that lead to essential changes in the country's macroeconomic structure. They concluded that the news of changes in the government caused positive abnormal returns in the Indian stock market.

The impact of the 2019 general election results on the Indian Stock Market in its various sectors revealed that the NIFTY market index gained significantly during the general election (Gour & Singh, 2020). They analysed that the market reacted positively during GEs, but the impact was not the same between any two elections, even when the same party came into power for the second time. The “semi-strong” form of the EMH proved to be true in the context of emerging markets like India. Semi-strong form assumes that stock prices reflect all publically available information, which includes historical price and volume. It assumes that the information is instantaneously priced in.

An excellent economic performance increases the chances of re-election for an incumbent candidate or party (Chavali et al., 2020). Their study revealed a positive market reaction to GEs regarding average abnormal returns (AAR) percentage in the Indian stock market. The AAR was computed for the 82 days around the event day of the election results during 2014 and 2019. Their study confirmed that elections positively impact the stock market performance in the Indian context. However, it was observed that the stock market reaction was more pronounced when a party came to power for the first time than for the second time consecutively. Their findings are in contrast to the findings of Gour and Singh.

"The mood of the investors depends on the nature of the political alliance whether it is communist, socialist, or capitalist dependent". Hence, on the principles followed by the alliance, the volatility differs in the Indian Stock Market (Selvakumar, n.d.).

In contrast to the majority of research papers that found evidence of abnormal returns and volatility in stock markets due to GEs in a country, few researchers found no significant impact of GEs on abnormal returns in their stock markets. For instance, a research paper: "Impact of 2019 General Election on Abnormal Return in Indonesia" (Erde et al., n.d.), determined the impact of the 2019 Indonesian General Election on abnormal stock returns. Using the event study method with a sample consisting of 93 companies that are listed on the Kompas100 index, calculating the expected return in the mean adjusted model, their results indicated that the 2019 General Election caused a negative but insignificant impact on abnormal return before and after the election. They reasoned that investors were not surprised by the results as they were already expecting the general election results, and they negatively perceived the 2019 GE due to fraud and scandals surrounding the 2019 Indonesian GE.

Yet another research study found no significant impact of GE on their stock markets, as explained in the paper "Abnormal Return Analysis Before and after General Election in Asia"

(Lesmana & Sumani, 2022). It compared the stock market activities of four Asian countries (Indonesia, Malaysia, Singapore, and Pakistan) that conduct GE, with the condition that the GE in those countries is completed in a single day. According to the researchers, no significant difference was observed between the average abnormal returns before and after the general election event in the last five general elections for all countries. It could occur due to factors such as investor anticipation, rational investor behaviour, and the market's efficiency in reflecting expectations.

2.1.4 Behavioural Biases

People make decisions with inadequate and imperfect information, as well as limited cognitive capacity, in the real world. Heuristics are mental shortcuts for repeated tasks that minimise effort and optimise performance, which can lead to behavioural biases.

Tversky and Kahneman introduced the notions of “Heuristic and Bias”. They explained that subjective probability assessment is akin to judging physical quantities like distance or size. These judgments are based on limited data and processed using heuristic rules. For example, the perceived distance of an object is affected by its clarity; sharper objects appear closer. This general rule can lead to errors: distances may be overestimated in poor visibility when objects look blurred, while they can be underestimated in good visibility due to increased sharpness. Thus, relying on clarity can result in biases similar to intuitive probability judgments (Tversky & Kahneman, 1974). As Kahneman explains, “Substitution” is an answer to a more accessible and alternate-related question for a tricky question in which one doesn't find the answer quickly. This idea of his became the core of the heuristics and biases theories. Heuristic simplification stems from various biases, the most prevalent being the "Representativeness" and "Availability” biases.

Representative Bias: Individuals often assess probabilities and odds based on their preexisting beliefs, even when conclusions lack statistical validity. A prime example is the "Gambler's Fallacy," where people believe luck in gambling occurs in streaks. This belief is shaped more by psychological factors than mathematical truths, making streaks statistically meaningless.

Observers expect the statistics of a sample to closely resemble (or “represent”) the corresponding population parameters, even when the sample is small (Kahneman et al., 2001). The “Representation hypothesis” soon led to the idea of a “Representativeness heuristic,” according to which some probability judgments (the likelihood that X is a Y) are mediated by assessments of resemblance (the degree to which X “looks like” a Y). This originated the idea of heuristics, which states that a difficult question is answered by substituting an answer for an easier one.

“Sample-size neglect” originates from representative heuristics based on the flawed belief that small samples accurately reflect larger populations. This assumption lacks scientific validity. Sample-size neglect occurs when investors evaluate the likelihood of a specific investment outcome without carefully considering the sample size of the data they use. They mistakenly believe that small sample sizes can represent the larger population or "true" data. This phenomenon is also called “The Law of Small Numbers” (Tversky & Kahneman, 1974). For instance, consider a game of squash, which can be played to either nine or fifteen points. A crucial principle from probability theory is that the larger the number of rounds played (such as fifteen rounds rather than nine), the higher the likelihood of the expected outcome being realised (i.e., victory for the stronger player). Therefore, you should prefer the longer game if you view yourself as the stronger competitor. Conversely, considering yourself the weaker player, the shorter game would be more advantageous.

Interestingly, many individuals might assume that winning against an opponent in either a nine-point or a fifteen-point match equally showcases their squash skill. This common misconception underscores the influence of sample-size neglect bias. Applying the law of large numbers to a small sample can yield skewed estimates, a concept that can be seamlessly extended to finance. They considered intuitive predictions to follow judgmental heuristic-representativeness. Through this heuristic method, people can predict the most representative outcome of the evidence. Consequently, intuitive predictions are insensitive to the reliability of the evidence or to the prior probability of the result, violating the logic of statistical prediction.

Availability bias: It is a prevalent psychological shortcut (Tversky & Kahneman, 1973b), that influence decision-making. The availability heuristic asserts that individuals estimate frequencies or probabilities and, therefore, overweight current information due to the ease with which similar instances or connections can be brought to their minds rather than processing all relevant information. Exaggerated and extensive formats of reporting on media, exceptionally high trading volumes and returns of stocks tend to grab investors' attention, stimulating excessive trading in such stocks.

According to the esteemed neuroscientist Andrew Lo (n.d.), an alternative to the Efficient Market Hypothesis (EMH) is the Adaptive Market Hypothesis (AMH), which posits that individuals behave in distinct ways and are prone to making mistakes. In this framework, competition fosters adaptation and innovation, while natural selection influences market dynamics, ultimately establishing that evolution plays a key role in shaping market behaviour.

Bounded Rationality: Nobel Prize winner Herbert Simon introduced the concept of "Bounded rationality" (Simon, 1990), which refers to the idea that when people make decisions, they are limited by their cognitive abilities, the information available, and the costs and time required for information gathering. People cannot perfectly retrieve relevant information from memory (Pennington & Hastie, n.d.).

“People underweight the probabilities of contingencies that are not explicitly available for consideration” (Slovic et al., 2013). This suggests a kind of overconfidence and apparent market overreaction when unforeseen contingencies do occur. “Overconfidence” is a pervasive behaviour. It is concluded in many research studies, though not conclusively, that overconfidence bias triggers excessive trading in some select stocks that investors follow. “Overconfidence” is unwarranted faith in one’s intuitive reasoning, judgments, and cognitive abilities. People are poorly calibrated in estimating probabilities—events they think are sure to happen are often far less than 100 per cent certain to occur.

Professor David Hirshleifer of Ohio State University cites Edwards to be the originator of the “Conservatism Bias” where people stick to their own beliefs and forecasts, thus not willing to accept any information which might be helpful for their rational decision-making.. He noted that one explanation for conservatism is that processing new information and updating beliefs is cognitively costly. He said that information presented in a cognitively costly form, such as abstract and statistical information, is weighted less. People tend to cling tenaciously to a view or a forecast.

Once a position has been stated, most people find it difficult to move away from that view. When movement does occur, it does so only very slowly. The "status quo" bias may stem from a conservatism bias.

Individuals demonstrating "Regret Aversion" tend to refrain from making decisive actions due to their fear that, in hindsight, whatever course they select will prove less than optimal. This bias seeks to forestall the pain of regret associated with poor decision-making. People suffering from regret aversion bias tend to hesitate most at moments that require aggressive behaviour. Regret-averse individuals attempt to avoid distress arising from two types of mistakes: errors of commission and errors of omission. "Errors of commission" occur when we take misguided actions. "Errors of omission" arise from misguided inaction, that is, opportunities overlooked or foregone. Regret is most palpable and takes the greatest toll on decision-making when the outcomes of foregone alternatives are highly visible or readily accessible. Regret becomes less influential when the consequences of mistakes are less discernible. Regret theory bears some similarities to "Prospect theory" by Kahneman and Tversky, and many of its predictions are consistent with the empirical observations of human behaviour that constitute the building blocks of prospect theory. Regret aversion can cause investors to be too conservative in their investment choices.

Regret aversion can cause "Herd behaviour" because, for some investors, buying into an apparent mass consensus can limit the potential for future regret (Chandra, 2020). "Hindsight Bias" may also emanate from the Regret Aversion bias."Ajzen and Fishbein's Theory of Reasoned Action" (Al-Suqri & Al-Kharusi, 2015) provides an overview of the Theory of Reasoned Actions

(TRA) and the main variants of the model. The theory elucidates the relationship between attitudes, intentions, and behaviours, especially within social psychology. At its foundation, the TRA asserts that an individual’s intention to engage in a behaviour is the primary predictor of whether they will perform that behaviour. Two crucial factors shape this intention:

- Attitude toward the Behaviour: This pertains to the individual’s positive or negative evaluation of the behaviour. If a person believes that engaging in the behaviour will result in favourable outcomes—such as the health benefits associated with regular exercise—they are more likely to cultivate a positive attitude toward it.

- Subjective Norms: This encompasses the perceived social pressures to engage in or refrain from the behaviour. This aspect reflects the influence of others' expectations, including those of family, friends, and society. For example, if someone perceives that key individuals expect them to exercise, this social pressure can strengthen their intention. These components collectively lay the groundwork for predicting an individual's behavioural intentions. The TRA suggests we can effectively promote behaviour change by understanding and influencing attitudes and subjective norms. This theory has broad applications in various domains, including health education, marketing, and policymaking. Nonetheless, it is essential to recognise the limitations of the TRA; for instance, it may not fully address behaviours that are not entirely under volitional control or those influenced by external factors such as habits or environmental constraints.

Later, Ajzen (Ajzen, 2011) expanded upon TRA to develop the Theory of Planned Behaviour (TPB), which includes perceived behavioural control as an additional factor influencing behavioural intentions. This expansion has allowed for a more comprehensive understanding of the complexities involved in human behaviour.

Human brains have evolved over the past few thousand years to prioritise logical and rational thinking. However, this development occurred relatively recently in the grand scale of evolution compared to the millions of years of development of our emotional limbic brain system. Therefore, expecting ourselves to behave rationally, especially when making financial decisions, may not align with our evolutionary history. The hardwired signalling system in human brains is also the cause of many errors in our decisions under uncertain situations, which are reflected in our actions in all walks of life, be it social, cultural, legal or financial. This insight into our evolutionary past sheds new light on our financial decision-making processes. (Chandra, 2020)

Neurofinance is an emerging field that combines economics, neuroscience, and psychology to understand the foundations of people's financial decisions better. Monetary gains or losses are not just financial outcomes; they also have significant psychological and biological impacts on individuals. People tend to feel the anticipation of a gain or loss more intensely than the actual event itself. There are two types of goal-oriented behaviours: reward-seeking and loss avoidance. These behaviours are regulated by neural circuits in the human brain that involve emotion, cognition, and action. When one of these behaviours is dominant, the other tends to diminish (Chandra, 2020).

2.1.5 Behavioural Biases in Finance

The field of BF has undergone significant evolution, primarily informed by critical contributions from psychologists, economists, and educators (Antony, 2020). This evolution is marked by seminal works and theories that have been instrumental in shaping the foundational concepts of the discipline:

- Gustav Le Bon (1895) provided one of the earliest comprehensive analyses of collective behaviour in “The Crowd: A Study of the Popular Mind,” wherein he introduced key concepts such as herd behaviour and crowd psychology. This foundational work has been pivotal in understanding individual behaviour within group dynamics.

- GC Seldon (1912), in his exploration of psychological factors affecting stock market dynamics titled “The Psychology of the Stock Market,” posited that stock price fluctuations are predominantly influenced by the mental attitudes and emotions of investors and traders, thereby elucidating the psychological underpinnings of market behaviour.

- Burrell (1951), in an influential article titled “The Possibility of Experimental Approach to Investment Analysis,” published in the Journal of Finance, advocated for applying scientific methodologies in investment decision-making. This pivotal text examined how human behavioural patterns manifest in stock market operations.

- Leon Festinger's (1957) introduction of the concept of cognitive dissonance in “A Theory of Cognitive Dissonance” has substantially contributed to understanding the psychological tensions investors face when confronted with conflicting information.

- The collaborative work of Daniel Kahneman and Amos Tversky (1973 onwards) has introduced numerous foundational concepts in BF. Their series of publications include: “A Heuristic for Judging Frequency and Probability” (1973), “Judgment Under Uncertainty: Heuristics and Biases” (1974), “Prospect Theory: An Analysis of Decision Under Risk” (1979), “Rational Choice and the Framing of Decisions” (1986), and “Advances in Prospect Theory: Cumulative Representation of Uncertainty” (1992). Additionally, Tversky and Gilovich’s examination of the “hot hand” phenomenon in “The Hot Hand: Statistical Reality or Cognitive Illusion?” (1989) underscores the cognitive biases that influence investor behaviour.

- William F. De Bondt and Richard Thaler (1985), in their work on market “overreaction,” elucidated the tendency of markets to overreact to new information, thereby contributing significantly to the discourse on market efficiency and behavioural biases.

- Hersh Shefrin and Meir Statman (1985), through their article titled “The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence,” published in the “Journal of Finance”, provided empirical insights into investor behaviour by introducing the concept of "regret aversion." In a subsequent study, Shefrin and Statman (2000) presented “Behavioural Portfolio Theory,” which expanded traditional CAPMs by incorporating behavioural aspects into portfolio management strategies.

- Robert Olsen (1998), in “Behavioural Finance and Its Implications for Stock Price Volatility,” published in the Financial Analysts Journal, conducted an extensive examination of the principles underlying behavioural finance, contextualising its impact on stock market volatility.

- Robert J. Shiller (2000), in “Irrational Exuberance”, further explored the concept of anchoring, highlighting how psychological factors influence market behaviours.
- J. Fernandes, J.I. Pena, and T. Benjamin (2009) classified behavioural biases into cognitive and emotional categories in their study “Behavioural Finance and Estimation of Risk in Stochastic Portfolio Optimization." This thereby contributed to a more nuanced understanding of decision-making processes in finance. This body of work collectively enriches the field of behavioural finance, providing critical insights into the interplay of psychological factors and market dynamics.

The extensive work of these distinguished scholars underscores the significant influence of psychological factors on investor behaviour, thereby presenting a profound challenge to classical financial decision-making models and the theory of market efficiency. The aggregation of their findings illuminates the complex interactions between human biases and economic decision-making processes. Most human beings have limited cognitive capacity. In the evolution of the human brain, decision-making has relied on heuristics—quick shortcuts to making probability judgments of an outcome. These evolutionary traits lead to financial biases too, hence deviations in judgment and actions from rational methods. Classical financial theories assume that investors have all the information and make rational economic decisions that maximise their utility within their defined risk and reward “utility indifference curve”.

Similar to availability bias is “Recency bias”, which is a cognitive predisposition that causes people to recall and emphasise recent events and observations more prominently than those that occurred in the near or distant past. Investors track managers who produce temporary, outsized returns during a one-, two-, or three-year period and then make investment decisions based solely on such recent experiences. These investors fail to recognize the cyclical nature of asset class returns. So, for them, funds that have performed spectacularly in the very recent past appear unduly attractive. Recency bias is particularly prevalent during bull markets. Many investors implicitly presume, as they do during other cyclical peaks, that the market will continue its enormous gains forever. They all forget that bear markets can and do occur. Investors, who base decisions on their subjective short-term memories, hope that near-term history will continue to repeat itself. Intuitively, they argue that evidence gathered from recent experience narrows the range of potential outcomes, thereby enabling them to project future returns. This behaviour often creates misguided confidence and becomes a catalyst for error. If asked to identify the “best” mutual fund company, most investors will likely select a firm that engages in heavy advertising. In addition to maintaining a high public relations profile, these firms also “cherry-pick” the funds with the best results in their fund lineups, which makes this belief more “available” to be recalled. In reality, the companies that manage some of today’s highest-performing mutual funds undertake little to no advertising. Consumers who overlook these funds favouring more widely publicised alternatives may exemplify “Retrievability” or “Availability” bias.

Many Wall Street professionals are known to lean Republican, so a lot of people, given this readily available information, might speculate on availability bias that the markets benefit from Republican political hegemony. After all, why would so many well-informed individuals, whose livelihoods depend on the stock market's success, vote for Republicans if Democrats produced higher returns? According to a study done by the University of California at Los Angeles (Santa-Clara et al., 2001), for the 72 years between 1927 and 1999 showed that a broad stock index, similar to the Standard & Poor's (S&P) 500, returned approximately 9 per cent more a year on average on value weighted portfolios over one-month treasury bills, under a Democratic presidency than Republican presidency. Suppose your natural reaction to the question, "In the period 1927 to 1999, which political party's leadership correlated with higher stock market returns?" was to answer "Republican". In that case, you may be susceptible to availability and recency bias.

"Confirmation Bias", coined by Akerlof, George, Dickens, and William, in 1982, is the tendency of individuals to cling to preconceived notions and heavily rely on existing information. Consequently, they often alter new information to align with their opinions. This phenomenon can lead to irrational decision-making among investors, who may be biased toward familiar information while overlooking other pertinent data.

The "overconfidence bias" explains that investors often misjudge their ability to evaluate companies, leading them to overlook negative information that suggests they should avoid purchasing or consider selling a stock. They tend to engage in excessive trading, believing they possess superior knowledge, which often results in poor returns over time. Many also underestimate their downside risks, stemming from a lack of awareness of historical performance, which can lead to disappointing outcomes for their portfolios. Additionally, they frequently maintain under-diversified investments, taking on more risk than they realise without an adequate increase in their risk tolerance.

During their research at the University of California, Davis, Professors Brad Barber and Terrance Odean analysed the investment transactions of 35,000 households from 1991 to 1997, all of which used accounts at a well-known discount brokerage firm. Their findings were published in a 2001 paper titled “Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment” (Barber et al., n.d.). They concluded that men traded 45% more than women due to overconfidence. This trading behaviour reduced men’s net return by 2.65%, while women’s net return was diminished by 1.72%.

The "Self-deception" heuristic stems from an overconfidence bias in investors, which leads people to believe that their knowledge is more accurate than it actually is. Hence, their predictions of probabilities of events are too high or too low relative to the actual frequency. In finance, the effect of the self-deception bias leads to "Emotional" bias and forces errors like "regret" and "self-control". "Social" biases cause errors like "Herding” and “authority.”

Daniel Kahneman and Amos Tversky developed “Loss Aversion” bias in 1979 as part of the original prospect theory, specifically in response to the prospect theory’s observation that people generally feel a stronger impulse to avoid losses than to acquire gains (Kahneman & Tversky, 1979). They found that psychologically, the possibility of a loss is, on average, twice as powerful a motivator as the possibility of making a gain of equal magnitude; that is, a loss-averse person might demand, at minimum, a two-dollar gain for every dollar placed at risk. In this scenario, risks that don’t pay twice are unacceptable. The “loss aversion bias” causes investors to hold onto their losing investments and sell their winning ones, leading to suboptimal portfolio returns. People weigh all potential gains and losses with reference to their benchmark reference point.

Heuristic simplification, self-deception, emotional control, and social influence are the four main categories of biases that lead to errors in financial decision-making (Hirshleifer, 2001). For instance, biases such as familiarity, representativeness, availability, anchoring, and framing can all be categorised under the concept of “heuristic simplification” (information processing errors), while overconfidence, optimism, confirmation bias, hindsight bias, and cognitive dissonance can all be categorised under the concept of “self-deception bias.” Mood, self-control, and regret are categorised under “emotional biases,” and herding authority is categorised under “social biases.”

"Behavioural Finance is the study of the influence of psychological factors on financial markets' evolution. Financial investors exhibit a wide range of deviations from rational behaviour, which is why various factors explain market anomalies. (Ramona Birău, n.d.)

“Heuristic and Biases Related to Financial Investment and the Role of Behavioural Finance in Investment Decisions: A Case Study of Pakistan Stock Exchange” (YASIR KHAN et al., 2021), identified human biases which impact "Perceived Investment Performance". Their regression results found that the "herding effects," "over-confidence," "availability" bias, and "representativeness" have a positive and significant impact on investment performance. Their study is essential for individual investors, financial advisors, and companies' managers.

A similar study conducted by Javed, Bagh, and Razzaq investigated human biases: “herding effects, overconfidence, availability bias, and representativeness”, as Independent

Variables and perceived investment performance (PIP) as a dependent variable in the case of the Pakistan stock exchange (PSX), to identify if such biases impact PIP. They found a positive and significant impact on PIP (Javed et al., 2017).

Researchers, French and Poterba (Kenneth R. French & James M. Poterba, 1991) and Baxter and Jermann (Baxter et al., 1998) concluded that investors do not diversify their portfolios internationally well. This demonstrates a "Home bias" in investments. They are inclined to hold more domestic assets due to comfort and familiarity with the market; hence, their country-specific political risk will not be diluted in their portfolios. Rational factors may also influence investments in foreign stocks, including restrictions on capital movements, trading costs, and tax disadvantages.

Dasari used the researched heuristic-driven factors such as representativeness, herd behaviour, overconfidence, anchoring, and availability heuristics. His methodology applied Indian stock data as secondary data about heuristic factors collected from various journals. He concluded that heuristic, behavioural factors often influence investors' performance directly and indirectly in the capital market because they are not rational investment decisions (Dasari, 2020).

“Hyperbolic Discounting” biased individuals make inconsistent choices over time. In classical financial theories, applying a constant discounting rate to calculate the net present value of all future cash flows is systematically violated. The study shows that people’s valuation falls rapidly over small delay periods but then falls slowly for long delay periods. Nagy credits the originator of the concept of hyperbolic discounting, Samuelson, for his seminal work in 1937, “A Note on Measurement of Utility” (Nagy, 2010). Despite the same reasoning, people make choices that their future selves will not make today. For instance, one may choose USD 1200 in two years instead of 1000 a year from now. But he will probably select USD 1000 now instead of 1200 a year later. People also attach a value to the instant gratification factor in their financial decision-making.

The seminal research contributions of Hersh Shefrin and Meir Statman have significantly advanced the field of BF, particularly with their development of the "Behavioural Asset Pricing Models" (Shefrin & Statman, 1994) and the "Behavioural Portfolio Theory" (Shefrin & Statman, 2000). Their work critically integrates psychological factors into established financial theories, specifically the CAPM and MPT, thereby challenging traditional views of investor behaviour and decision-making processes.

The BPT notably builds upon existing psychological theories, particularly Lopes' Safety Potential/Aspiration (SP/A) theory, formulated in 1987, and Kahneman and Tversky's groundbreaking “Prospect Theory” established in 1979. This theory is pivotal in illustrating how investors' risk preferences are not static but rather influenced by contextual reference points established through individual experiences and beliefs. This introduces a critical concept into financial decision-making: reference points are fluid and can shift over time, impacting how investors assess potential gains and losses. Central to the Prospect theory is the duality in investors' risk attitudes, where they display risk-seeking behaviour in the face of possible losses while exhibiting risk aversion when confronted with the prospect of gains. This psychological nuance reveals that investors endure disproportionately greater emotional distress from losses than the satisfaction derived from equivalent gains. This asymmetrical reaction contradicts the classical finance assumption of rationality and risk aversion among investors, suggesting that emotional factors heavily influence financial choices (Kahneman & Tversky, 1979).

In expanding on traditional investment frameworks, the SP/A theory introduces two essential constructs for understanding investor behaviour during portfolio construction: Safety Potential (S), Potential (P), and Aspiration (A). The Safety (S) criterion elucidates how investors possess a fundamental desire to protect their capital, perceiving it as essential for their survival or sustenance, which lead them to adopt a more conservative, risk-averse approach toward investment decisions. In contrast, the potential (P) criterion captures the investors' ambition to achieve a higher level of wealth as risk-seekers. Aspiration (A) strives for the achievement of set goals (Lopes & Oden, 1999).

One of the significant innovations BPT presents is its conceptualisation of portfolios as multiple layered constructs rather than a singular entity, as posited by MPT. In the BPT framework, investors are recomended to maintain various portfolios tailored to distinct, multifaceted goals, each operating under different expected return profiles and risk tolerance levels. This results in a portfolio structure often visualised as a layered pyramid. At the base are low-risk investments, which serve to satisfy the investor's basic security needs, while at the apex are riskier investments aimed at fulfilling higher aspirations for wealth accumulation.

Moreover, the behavioural model reframes the understanding of asset pricing by incorporating expressive and emotional benefits alongside traditional utilitarian considerations. This broadens the dimensions through which investors evaluate their choices. Expressive benefits relate to the satisfaction derived from investments that resonate with societal values or norms, while emotional benefits encompass the intrinsic fulfillment patients realise from their investment choices. For example, environmentally conscious investors might prioritise stocks from sustainable companies, deriving satisfaction from potential financial returns and aligning their investments with personal values and broader societal implications. Conversely, investments in industries like tobacco may be eschewed due to strong personal narratives surrounding health impacts or ethical concerns indicative of the emotional dimensions influencing financial decision-making.

Ultimately, the BPT and BAPM emphasise that investor behaviour is complex and multifaceted, profoundly influenced by psychological motivations, emotional responses, and individual circumstances. Their framework facilitates a deeper understanding of investor dynamics, revealing that financial portfolios are not merely collections of financial assets but rather embodiments of personal aspirations, social identities, and emotional narratives, collectively shaping how individuals navigate the intricate landscape of investment decision-making.

2.2 Summary

The country's future economic and business environment significantly influences the stock markets, primarily determined by the government’s economic policies. For example, fiscal policies encompassing government spending and taxation substantially impact the overall scale of the economy, as seen in India.

However, in India, the government functions on a five-year term, with general elections held every five years to form new administrations. These elections involve various parties with differing economic ideologies vying for power. As a result, in the lead-up to these elections, the markets evaluate the outgoing government's financial performance while anticipating the incoming administration's policies. While financial analysts endeavour to apply rational financial models that incorporate all available information affecting intrinsic valuations, their biases frequently lead to inconsistencies in their assumptions, predictions, and resultant outcomes. This deviation from rational thought can culminate in predictable and anomalous market pricing during Indian GEs.

Behavioural biases observed in individuals often manifest multiple biases, which complicates the identification of one specific bias responsible for a given effect. To navigate this complexity, the current research is designed to study the most prevalent human financial biases under two overarching categories of human biases: “Emotional” and “Cognitive”. Emotional biases are reaction biases from situations that induce specific emotions in people due to the “reactive brain system”. Cognitive biases originate from the “reflective system of mind,” which is the heuristics and shortcuts developed by the human brain to execute known and repeated tasks. Citing Keith Stanovic and Richard West in his book, “Behavioural Biases”, Prassana Chandra (Chandra, 2020) refers to the reactive brain system as “System 1” and the reflective brain system as “System 2”. System 1 operates automatically and rapidly. In contrast, system 2 is effortful, deliberate and slow. This framing of bias categorisation provides a more comprehensive understanding of the issues and helps test the hypothesis more efficiently.

Classical financial pricing models empirically appear to be flawed by their assumptions that people behave rationally when pricing stocks. Therefore, the scope of market mispricing is negligible. The literature review shows a causal relationship between the financial biases of investors and abnormal stock market pricing during political events such as general elections.

The BPT and BAPM assert that investor behaviour is complex and shaped by psychological motivations, emotional responses, and personal circumstances. Their framework reveals that financial portfolios are not just collections of assets; they embody personal aspirations, social identities, and emotional narratives that influence how individuals approach investment decision-making.

The current research is centred on expanding our understanding of behavioural finance, which posits that emotional factors and cognitive biases influence the financial decision-making processes of individuals. Despite its growing significance, several research questions remain unexplored in the existing literature, particularly within emerging markets such as India. This study specifically addresses these gaps by conducting scientific tests on the historical data of the Indian stock market during the past five general elections from 2000 to 2024. It focuses on the impact of investors' broad bias categories during general elections, which cause stock markets to exhibit heightened volatility and abnormally high returns, as revealed through this extensive research analysis. By examining data from the last five Indian general elections, spanning twenty-four years, including the recent 2024 general election, and conducting a survey in May 2024, when the election took place, this research provides a comprehensive examination of how such significant political events influence market behaviour and individual investment strategies. This extensive timeframe allows for a thorough analysis that captures shifts in market dynamics and investor psychology across multiple election cycles. By integrating findings from behavioural finance with real-world events, the study aims to illuminate the patterns of financial biases exhibited by investors, ultimately contributing to a richer theoretical framework in the field of behavioural finance. The insights garnered from this research could inform academic discourse, practical investment strategies, regulatory insights, and policy-making in financial markets.

CHAPTER III:

METHODOLOGY

3.1 Overview of the Research Problem

Unusual trends and recognisable patterns have emerged in the Indian stock markets during the Indian GEs, diverging from classical financial theories, which assert that stock prices adhere to a random walk theory, lacking predictability in future returns.

Empirical data from the Indian stock markets indicates that during the year surrounding the Indian GEs, their returns tend to surpass the long-term average observed over the past two decades. Furthermore, volatility in the stock markets notably increases for about a month around the announcement of GE's results. These discernible patterns suggest a potential link to the biases of investors, which can lead to irrational financial decisions during these periods. Such phenomena align with BF theories, which argue for a shift towards alternative financial models that incorporate investor biases in market pricing.

The proposed research is grounded in a fundamental principle articulated by BF experts: "Investors are normal beings, not rational beings." This viewpoint recognises that the reflective and reflexive brain systems in humans have evolved for our survival. The reflective system is cognitive in nature, while the reflexive system is rooted in emotion. Given limited time and cognitive resources, individuals often find it challenging to analyse available information optimally, leading to cognitive biases (Simon.A, 1990). Charles Darwin posited that traits aiding a species' survival become innate characteristics over time, with emotions being a key component.

In the book “Behavioural Finance”, Chandra presents some intersting physiological theories including the James-Lange theory, according to which an external stimulus triggers a physiological response, which subsequently leads to an emotional reaction based on the individual's interpretation of that physiological response. Conversely, the Cannon-Bard theory asserts that both emotional and physiological responses occur simultaneously when the thalamus transmits messages to the brain in reaction to a stimulus.

These systems significantly contribute to various biases and heuristics that influence our decision-making process, often hindering our ability to act with complete rationality in the financial markets.

3.2 Theoretical Construct and Operationalisation

Numerous theories within the realm of BF, as delineated in the literature review, have been conceptualised by researchers through a postpositivist lens. This approach facilitates the observation, measurement, and analysis of the objective realities of investor biases that challenge classical finance theories predicated on the assumption of rationality and utility-maximizing behaviour among investors. Postpositivists maintain a deterministic perspective, suggesting that causal relationships govern observable outcomes. The present research adopts a parallel stance to assess the veracity of human biases as contributors to irrational market price fluctuations while humbly acknowledging the limitations in pursuing absolute truth and the complexities involved in fully understanding human behaviour and decision-making.

This research used traditional scientific methodologies to systematically gather, validate, wrangle, code, test, and analyse the relevant data. The study focuses on the movements of the Indian stock market in the context of the Indian GEs, statistically examining predictable patterns and elucidating the causes of anomalous volatility and returns associated with investor biases. Furthermore, the analysis includes demographic data on investors, along with their financial biases, using descriptive, statistical, and inferential modelling techniques to establish significant correlations between the variables.

This research aims to validate its central hypothesis (H), which asserts that GEs in India induce substantial volatility in their stock markets, particularly during a short one-month period encompassing the announcement of the election results. Investors are often influenced by their inherent psychological biases, which can lead to atypical market pricing. Once the uncertainty regarding the electoral outcome is resolved, the stock market typically experiences a pronounced return in the medium term, within one year.

Conversely, the null hypothesis (H0) proposes that the Indian stock markets function efficiently, driven by rational investors who adeptly and accurately incorporate all available information into stock prices. These investors remain impervious to emotional or cognitive biases that otherwise cause abnormal market volatility and price predictability during Indian GEs."

The null hypothesis aligns with the EMH prevalent in traditional finance discourse.

To enhance clarity in examining the research hypothesis (H), it is subdivided into three distinct components: H1, H2, and H3, which form the basis of three specific sub-hypotheses.

- H1 posits that "The stock markets in India exhibit an abnormally high positive return during the year surrounding its general elections, significantly exceeding annual returns observed during non-election periods."
- H2 states that "The Indian stock markets display significantly elevated volatility during the month surrounding the announcement of the general election results, surpassing volatility observed during other short-term periods."
- H3 asserts, "Financial biases in investors cause the abnormal market behaviour during Indian GEs."

For statistical tests and interpretation of the results of each of the three sub-hypotheses, their respective null hypotheses, which form part of the central null hypothesis (H0), are explicitly defined in the further sections of the report as appropriate.

“Knowledge is conjectural—Absolute truth can never be found” (N.C, 2000). That is why researchers do not prove a hypothesis; instead, they indicate a failure to reject it. Therefore, H1, H2, and H3 were statistically tested independently to reject the null hypothesis H0.

3.3 Research Purpose and Questions

The two key research questions that the current study seeks to address are:

1. Do the Indian stock markets deviate from their intrinsic pricing, as outlined by traditional financial theories, during periods of political uncertainty, such as during the General Elections in India?

2. Do investors exhibit financial biases in their decision-making processes, leading to the mispricing of stock market valuations?

The study focused on mispricing in the Indian stock markets, particularly during the five GEs from 2000 to 2024. The central theme of the research was to first establish statistically that mispricing in stock markets does occur and subsequently explain how uncertainties surrounding elections trigger various investor biases that cause such mispricing.

Investor behaviour during election periods is particularly interesting because the fluctuating political landscape can evoke strong emotional responses, such as fear or exuberance, which may overshadow rational analysis. Cognitive biases, such as over-optimism or representativeness, can also play a crucial role, as investors may cling to pre-existing beliefs or make decisions based on incomplete information.

To rigorously assess the impact of these biases on Indian stock markets, the research analysed market volatility over a month around the election results and tracked abnormal market returns over the year around the GE events. The study aimed to uncover the underlying causes of market phenomena observed during these electoral periods by employing various statistical approaches aimed at generalising the phenomena.

The findings are instrumental for investors and regulators, offering insights into investors' financial biases and navigating the complex dynamics of the stock market during periods of political uncertainty. By recognising the potential for significant mispricing due to emotional and cognitive biases, investors can develop strategies that enable more informed decision-making in the stock market during politically uncertain times. Furthermore, the study lays a foundation for future research aimed at managing these biases. Understanding how external factors can influence investor behaviour is key to improving the overall financial efficiency of a system. The purpose of this research extends beyond the immediate context of Indian GE and its stock markets, suggesting that similar principles could apply in different financial situations and under various uncertain conditions, thereby enriching the broader field of BF.

3.4 Research Design

The study addressed its two research questions by analysing the results of the three sub-hypotheses: H1, H2, and H3. The first research question was answered by testing hypotheses H1 and H2, while the second research question was investigated by testing and analysing hypothesis H3.

Statistically rejecting the null hypothesis (H0) in favour of hypotheses H1 and H2 supports research question one, which suggests that stock markets experience mispricings during the Indian General Election years, leading to significant short-term volatility and mid-term price predictability. To investigate these hypotheses, the researcher utilised two quantitative datasets for statistical comparison, obtained from secondary historical data of the Indian stock market from 2000 to 2024. The datasets, which focused on the Indian General Election periods, represented the alternative hypothesis of the research. In contrast, the other datasets used for comparison comprised data from non-election periods, representing the null hypothesis. Two-sample t-tests were employed to compare the alternative hypothesis datasets to the null datasets, considering that the test accounts for effect size, sample size, and variability between the two datasets in comparison.

A quantitative survey research methodology was utilised to generate data of investors' biases to represent the alternate hypothesis of the research (H3). The aim was to establish a significant prevalence of overall bias in investors, including the emotional and cognitive biases. In contrast, a 0 (zero) bias value represents the null hypothesis that the traditional financial theories claim. They assume that investors are rational decision-makers devoid of any bias.

The survey questions were framed to capture investors' biases and grouped into broader categories: "Emotional," "Cognitive," and "Overall." The book "Behavioural Finance and Wealth Management" (Pompian, n.d.) served as a valuable inspiration and reference in crafting the survey questionnaire to effectively identify and capture common financial biases among investors. This approach enhanced the validity and reliability of the questionnaire. Furthermore, face and content validity of the instrument were assessed through peer reviews.

Statistical comparisons of the mean values of the group biases were conducted against the mean bias value in the population (assumed to be 0 in the null hypothesis, that is, on average, investors are rational), using a one-sample, right-tailed t-test method.

Chi-square tests were employed to investigate potential associations between the group biases and the demographic profiles of investors. For this purpose, the survey data was transformed into categorical data through feature engineering techniques. Additionally, Cramer's V tests were performed to assess the strength of the associations wherever a statistically significant relationships were identified.

Furthermore, linear regression models were applied to the survey data to establish and analyse correlations of investors' biases with their demographic profiles.

By utilising the appropriate libraries and data analysis capabilities, "R" and “R Studio” proved more effective in managing and conducting the quantitative tests and analysis for the large data sets used in testing H1 and H2. In contrast, the quantitative survey data for the statistical tests of hypothesis H3 could be executed using the simple-to-use “MS Excel” tools. However, the demographic analysis of the survey data was performed using R, which is better suited for data visualisation and model execution.

3.4.1 Research Methodology for Hypothesis 1

The “NIFTRI” is an Indian market return index represented by the top fifty listed companies on the National Stock Exchange of India. It is a free-float market capitalization-weighted index that incorporates dividends distributed to shareholders by the companies. As such, this index provides a comprehensive representation of India's stock market returns.

Daily closing values of the NIFTRI from June 30, 1999, to December 1, 2024 (source: www.investing.com), were used to create two subsets of annual market return data: one of the five Indian GE years (2004, 2009, 2014, 2019 and 2024), while the other, of the non-election period from 2000 to 2024. Therefore, a five-point data subset was derived to represent the alternate hypothesis H1. These five data points were calculated using NIFTRI’s values market data from six months before and six months after the election month (coincidentally, May happened to be the election month for all five Indian general elections years), which were considered as its entry and exit points, respectively. The “exit points” were calculated as the average of NIFTRI closing price from 1st November to 30th November of the election year, while the “entry points” were calculated based on the average of NIFTRI closing price from 1st November to 1st December of the preceding year of the GE. The entry and exit values were averaged to mitigate the influence of any erratic market fluctuations on specific dates. For example,

The first data point in the election-year subset was for GE year 2004, computed as:

Exit point = (Average of NIFTRI closing price between 1st November 2004 and 1st December 2004) ÷ Entry point (Average NIFTRI closing price between 1st November 2003 and 1st December 2003).

The second data point for GE 2009 was similarly calculated as:

Exit point (Average NIFTRI closing price between 1st November 2009 and 1st December 2009) ÷ Entry (Average NIFTRI closing price between 1st November 2008 and 1st December 2008).

The calculation pattern was followed until the third, fourth and fifth data points for GE 2014, 2020 and 2024 were derived for H1.

The non-election year data subset representing the null hypothesis consisted of data points reflecting the one-year NIFTRI return on a “daily rolling basis” from 1st December 1999 to 30th October 2023. This effectively meant that the annual return was calculated for every trading day. This subset represents the null, excluding all data points included in the 2004, 2009, 2014, 2019, and 2024 election period data set. On average, the Indian stock exchange experiences approximately 252 trading days per year, resulting in 4,989 data points corresponding to one-year market returns within the non-election period dataset. Consequently, averaging market closing prices for the entry and exit points was unnecessary. For example:

The first data point was calculated as:

Exit point (NIFTRI closing on 30th November 2000) ÷ the Entry point (the NIFTRI closing price on the 252nd trading day before the entry date).

The second data point was determined as follows:

Exit point (the NIFTRI closing value on 1st December 2000) ÷ the entry point (the NIFTRI closing value on the 252nd trading day before 1st December 2000).

Similarly, all other data points were calculated until the last data point for the non-election year subset was derived as follows:

The exit point (the NIFTRI closing on 31st October 2023) was divided by the entry point (the NIFTRI closing on the 252nd trading day before the exit point on 31st October 2023).

The non-election year data subset included precisely 4,989 data points, while the election year data subset contained 5 data points. To compare the effects between these two datasets (election and non-election years), we utilised the “Student's two-sample directional t-test” method, as both the datasets displayed similar variances. (Appendix B.4 Additional Support for using Two Sample t-test).

3.4.2 Research Methodology for Hypothesis 2

Hypothesis H2 examined the volatility of the Indian stock market for approximately a month (an average of twenty-one trading days) around the Indian GE results.

The India Volatility Index (IndiaVIX) is a reliable gauge of market return volatility on the National Stock Exchange of India. Data for the IndiaVIX, which commenced on August 1, 2008, was obtained from the National Stock Exchange's website, covering the period from August 1, 2008, to May 31, 2024 (source www.nse.com). The IndiaVIX provides an overview of market volatility over the next thirty days. A high value of IndiaVIX is indicative of heightened market fear. This index is derived by analysing the “bid” and “ask” prices of near and next-month options contracts for the NIFTY 50 index on the NSE. The calculation of IndiaVIX follows the formula:

$$India\,VIX = 100 \times \sqrt{(}\sum(Weighted\ Implied\ Volatility\ Squared) \div Total\ Weight)$$

Weighted Implied Volatility is the cumulative sum of the squared implied volatilities, each multiplied by its corresponding weight. Implied volatility is an estimate of how much an asset’s price will change in the future calculated using the Black & Scholes formula.

Total Weight represents the total open interest of all options utilised in the calculation. The India VIX ultimately measures the expected market volatility over the forthcoming thirty days.

Four subsets of short-term volatility data corresponding to the four Indian GE months (May 2009, May 2014, May 2019 and May 2024) representing the alternate hypothesis H2 were constructed to conduct statistical comparisons with corresponding null hypothesis subsets of short-term market volatility data from non-election periods spanning August 2008 to May 2024. Each subset of the election periods comprised daily market volatility data, as measured by ‘IndiaVIX’ values, collected from three weeks before the GE results announcement date to one week post-announcement, resulting in an average of twenty-one data points per subset. The result dates were on 16th May, 16th May, 23rd May, and 4th June for the election years 2009, 2014, 2019 and 2014, respectively.

Conversely, the non-election period data subsets of volatility were generated to encompass the timeframe from 1st August 2008 to 30th April 2024. These subsets consisted of precisely twenty-one data points obtained on a “daily rolling basis”. Any data points overlapping with the election period data were deliberately excluded from the subsets.

For instance, the first data point of the inaugural non-election subset was derived from the IndiaVIX value recorded on 1st August 2008, followed sequentially by the data point from 4th August 2008—given that 2nd and 3rd August 2008 were trading holidays—culminating in the twenty-first and the final data point of that subset taken from the IndiaVIX closing value on 29th August 2008. This methodology was replicated for the subsequent non-election subsets, starting with the IndiaVIX data from 4th August 2008 and proceeding daily (trading days) until the twenty-first data point taken from the closing value of India VIX on 1st September 2008. The process extended to create the final non-election subset, encapsulating the last twenty-one trading days of volatility data, concluding on 29th April 2024. Furthermore, any non-election data subset that included data points falling within the timeframes of the election period datasets was systematically excluded from consideration. Each of the four election-period data subsets was subjected to statistical comparisons using a two-sample, right-tailed t-test to evaluate the difference compared to each of the 3,864 non-election data subsets. The primary objective of this analysis was to determine the extent to which the election-year data subsets differed significantly from those representing non-election periods.

3.4.3 Research Methodology for Hypothesis 3

David Hirshleifer has organised judgment and decision biases into four primary categories: "Heuristic Simplification, Self-Deception, Emotion and Self-Control, and Social Interactions" (Hirshleifer, 2001a).

Additionally, researchers have categorised biases based on their violations of classical finance's axioms. Notably, the infringement of three essential axioms—"Dominance", "Invariance", and "Independence"—provides a sensible framework for specific studies.

The current research categorises investors' biases into three simplified categories: "Emotional Bias", "Cognitive Bias." And "Overall". This classification is informed by the concept of "Reflexive and Reflective Systems" of the brain (Stanovich et al., 2011), which aligns effectively with the emotional and cognitive biases of investors. The Overall-Bias group is merely a summation of these two bias categories.

"Do investors exhibit behavioural biases in investment decision making? A systematic review" (Zahera & Bansal, 2018) explored some of the most frequently studied biases in investment behaviour. Their findings highlighted the prevalence of various biases, with overconfidence being examined in twenty-four studies, the disposition effect in twenty studies, and herding in seventeen studies. Other biases included loss aversion (14 studies), framing (7 studies), mental accounting, representativeness, and confirmation bias, each of which was examined in six studies. Hindsight was featured in 5 studies, while anchoring was examined in 4. The house money effect and home bias were each studied in three instances, while self-attribution and regret aversion had two studies each. The endowment effect also appeared twice, and recency was examined once, resulting in a total of 123 studies on these behavioural biases.

Table 1: List of Prominent Biases in Investors

Cognitive vs Emotional Biases

C_Optimism	C_Gambler.Fallacy
C_Recency	C_Bounded.Rationality
C_OverOptimism	C_Representativeness
C_Home.Bias	C_MenAcc
E_Loss.Averse	E_Status.Quo
E_Self.Attrb	E_Herd
E_Disposition.Effect	E_SelfControl
E_Hindsight.Bias	E_OverConfidence

Group
Cognitive
Emotional

Source: Created by the author

The prefixes "C" and "E" in the independent bias names, as shown in Table 1, denote the two categories of biases: "C" representing cognitive biases and "E" representing emotional biases of investors.

A quantitative survey methodology was employed to systematically gather investor data through a structured set of closed-ended questions. This approach enabled the collection of objective and easily analysable data to compliment our research findings. To enhance the effectiveness of the survey, the initial design underwent significant revisions based on comprehensive feedback obtained from a pilot survey. This pilot involved a select group of respondents whose insights were invaluable in refining the survey instrument.

Among the key modifications made, the total number of questions was reduced from thirty-two to twenty-four. This was crucial in making the survey more focused and manageable for respondents, thereby increasing the likelihood of completion. Additionally, various questions were rephrased to eliminate any leading language that could inadvertently influence participant responses. This step was taken to ensure that the data collected accurately reflected the participants' genuine opinions and experiences, thereby enhancing the reliability of the survey.

Survey Questionnaire Design:

The current survey design attempted to capture most of the prevalent financial biases. Therefore, sixteen questions were carefully crafted to represent the all bias in investors, and eight questions were designed to record their demographic profiles. Specifically, the survey featured eight questions focused on capturing emotional biases, which included loss aversion, self-attribution, herding, the disposition effect, hindsight bias, and overconfidence bias. The remaining eight questions were targeted to capture cognitive biases, encompassing representativeness, availability, bounded rationality, home bias, mental accounting, optimism, and over-optimism. Furthermore, eight standard demographic questions were included to gather information about respondents’ names, ages, genders, income levels, qualifications, occupations, experience in the stock markets, and email addresses (optional) for demographic analysis.

The self-administered questionnaire finally consisted of 24 closed-ended questions: 8 questions designed to capture emotional biases, 8 addressing cognitive biases, and 8 to collect participants' demographic profiles. The demographic questions in the survey were included to facilitate supplementary analysis of respondents' biases with their demographic profiles.

The survey questions were framed in simple English, using relatable daily life situations of an investor, and presented with a maximum of four multiple-choice answers. Table 2 lists the names of the biases, the group to which each bias belongs, and a brief explanation of each bias, followed by the survey questions and their corresponding answer options. The answer code captured the investor's bias in a binary format, either "biased" or "unbiased".

Table 2: Survey Questions Design to Capture Prominent Biases of Investors

Bias Name (Group)	Optimism (Cognitive)
Brief Explanation of the Bias	Optimism is the general belief that positive outcomes are likely to occur. An individual's inclination towards optimism or pessimism is often an intrinsic part of their nature. Naturally, optimistic individuals may overlook signs and information indicating potential adverse outcomes, choosing to disregard them. A healthy balance between optimism and realism is essential for making well-informed, unbiased decisions.
Survey Question:1	From 1999 to 2023, if the compounded annual growth of NIFTRI50 in India has been around 14%, what compounded annualised growth of NIFTRI50 do you predict in the year 2024?
Answer Options	Well above 14% Above 14% Around 14% Below 14%
Coding the Answer Choice	Answer 1 or 2 - biased Answer 3 or 4 – unbiased

Bias Name (Group)	Gamblers fallacy (Cognitive)
Brief Explanation of the Bias	The gambler's fallacy is a form of representativeness bias that influences how individuals evaluate the characteristics of events or objects. This bias causes people to erroneously assume that certain events are more likely to happen based on their resemblance to past occurrences. Alternatively, they may believe

	that the law of averages must eventually align with mean reversion. As a consequence, they may make inaccurate predictions about future events.
Survey Question:2	The results of a coin toss from the first 5 tosses, in order of sequence are: 1) Tails 2)Tails 3) Heads 4)Heads 5) Heads What is the most likely outcome from the 6th toss of the coin?
Answer Options	Tails, because law of average should catch up after 2 times Tails and 3 times Heads in first 5 tosses Heads, because the momentum is in favour of Heads Can be either Tales or Heads with equal likelihood Cannot predict with more than 50% accuracy Answer 1or 2 – biased
Coding the Answer Choice	Answer 1or 2 – biased Answer 3 or 4 – unbiased

Bias Name (Group)	Recency bias (Cognitive)
Brief Explanation of the Bias	Investors often make decisions influenced by recency bias, concentrating on recent news while neglecting potentially valuable information from the more distant past. Those exhibiting this bias tend to view easily recalled possibilities as more probable than those less accessible or harder to conceptualise. This reliance on the availability heuristic results in judgments about the likelihood or frequency of events based on readily available information rather than on a complete, objective, or factual basis.
Survey Question:3	Which was the leading cause of human deaths in the world in 2023?
Answer Options	Deaths due to wars between countries Heart Diseases COVID19 None of the above
Coding the Answer Choice	Answers 1or 3 - biased Answer 2 or 4 - unbiased

Bias Name (Group)	Bounded rationality (Cognitive)
Brief Explanation of the Bias	This idea suggests that when people make decisions, they are constrained by their cognitive abilities, the information available to them, and the costs and time associated with gathering information.

Survey Question:4	Do you think that the events of geo-political unrest, like in Russia - Ukraine, Israel - Iran... have impacted the Indian stock markets in a negative way in the last 3-5 years?
Answer Options	Yes, otherwise Indian stock markets would have performed better than it actually did in the last 3-5 years No, geo-political unrests outside India do not impact Indian stock markets.
Coding the Answer Choice	Answer 1 – unbiased Answer 2 - biased

Bias Name (Group)	Loss Aversion Bias (Emotional)
Brief Explanation of the Bias	This concept highlights the tendency of individuals to respond differently to guaranteed losses compared to guaranteed gains. When presented with certain profits, people often exhibit a reluctance to take risks. In contrast, when faced with potential losses, they may be more inclined to engage in riskier behaviour. This phenomenon illustrates that individuals place a higher value on the certainty of avoiding losses than on the uncertainty of achieving gains
Survey Question:5	In a hypothetical situation, if you must choose an option, which option would you choose? Option A: A sure loss of Rupees 7,250 Option B: 75% chance of losing Rupees 10,000, with 25% chance of losing nothing.
Answer Options	Option A Option B
Coding the Answer Choice	Answer 1- unbiased Answer 2 – biased

Bias Name (Group)	Status Quo (Emotional)
Brief Explanation of the Bias	Status Quo represents a form of conservatism bias, where individuals tend to hold on to their existing beliefs or predictions, often overlooking new information. This bias can lead investors to underreact to recent developments, choosing instead to rely on impressions shaped by previous estimates rather than adapting to updated data
Survey Question:6	Assume that you get an opportunity to invest in a stock XYZ which can give you a return of 19% per year. Would you sell

	your existing stocks of ABC (which has been consistently giving you a 11% yearly returns) to invest in the XYZ stocks? (Assume that the risk involved in the XYZ is 1.5 times more than the risk in ABC stocks)
Answer Options	Yes, I will sell my ABC stocks to invest in XYZ stocks because of its better reward/risk ratio No, I will let not sell my performing ABC stocks to invest in a new XYZ stocks
Coding the Answer Choice	Answer 1- unbiased Answer 2 – biased

Bias Name (Group)	Self-Attribution bias (Emotional)
Brief Explanation of the Bias	Self-attribution bias explains that people attribute their success to their hard work and intelligence, while they blame their failure on the actions of others or to some outside factors.
Survey Question:7	Did you ever regret buying/selling a stock based on tips from any source/advisor?
Answer Options	Yes No
Coding the Answer Choice	Answer 1 – biased Answer 2 – unbiased

Bias Name (Group)	Herding (Emotional)
Brief Explanation of the Bias	Herding in the stock market refers to the tendency of investors to follow the decisions of other investors. This aspect of the investors is a subject of extensive research because they rely on the collective information they possess more than the private information. This can result in price deviations from the fundamental values and the risk of reduced returns
Survey Question:8	If you have to buy a sweet box for your boss on the way to his house, which sweet shop would you buy it from? A) shop which has many customers already waiting to buy the sweets B) shop where there is no customer seen in the shop (Assume that both the shops look equally good but you have no knowledge about the sweets in their shops)
Answer Options	Shop A Shop B
Coding the Answer Choice	Answer 1- biased Answer 2 - unbiased

Bias Name (Group)	Over Optimism (Cognitive)
Brief Explanation of the Bias	Over-optimism is an extreme form of Optimism
Survey Question:9	Currently, India is the 5th largest economy in the world in terms of GDP with USA at 27, China at 17.8, Germany at 4.4 Japan at 4.2 and India at 3.7 (in Trillion USD) Do you think that India will become the 3rd largest economy in the world by 2030?
Answer Options	Yes No
Coding the Answer Choice	Answer 1- Biased Answer 2- Unbiased

Bias Name (Group)	Representativeness (Cognitive)
Brief Explanation of the Bias	Representativeness refers to assessing the characteristics of an event or object and considering them similar to those of other events or objects. This makes them consider the event/object more likely to happen, which may or may not happen
Survey Question:10	If you were a given a chance to select one player, which player would you pick for the Indian men's team for the upcoming T-20 World Cup? Player 1: who has a very good long-term track record in domestic cricket, but is currently out of form. Player 2: who does not have a very good long-term record in domestic cricket, but he is in super form currently.
Answer Options	Player 1 Player 2
Coding the Answer Choice	Answer 1 – unbiased Answer 2 - biased

Bias Name (Group)	Home bias (Cognitive)
Brief Explanation of the Bias	Investors frequently feel a sense of affinity for their domestic companies, prompting them to invest in these firms even when their returns may be lower than those of their international counterparts. Consequently, this tendency fosters a preference for home bias among investors.
Survey Question:11	India is currently amongst the fastest-growing countries in terms of GDP. Will India offer the best opportunity to grow investors' wealth in its stock market in the next 5 years?

Answer Options	Yes No
Coding the Answer Choice	Answer 1–biased Answer 2 - unbiased

Bias Name (Group)	Mental Accounting (Cognitive)
Brief Explanation of the Bias	Mental accounting is the process by which individuals categorise and assess financial outcomes by organising their assets into separate mental accounts. For example, when someone loses a ticket and subsequently purchases a new one, they often perceive both costs as part of the same account, viewing them as consecutive losses. In contrast, these transactions are regarded separately when cash is lost and a ticket is bought. This separation tends to make the overall loss appear less significant as it is distributed across different accounts.
Survey Question:12	Assume that you win a prize money of INR 10,000 in a game of Tambola/Housie/Bingo during your family holiday. How would you use this prize money? Option1: Use it to pay for the regular expenses of the holiday so that I can save on the planned/budgeted expenses. Option 2: Spend it on shopping for the family because the regular expenses of the holiday are already planned/budgeted for.
Answer Options	Option 1 Option 2
Coding the Answer Choice	Answer 1–unbiased Answer 2 - biased

Bias Name (Group)	Disposition Effect (Emotional)
Brief Explanation of the Bias	Investors tend to sell superior selling stocks early to realise the gains and hold the losing stocks longer to delay the losses. The tendency to avoid losses is much more than the willingness to realise profits. The final decisions of the investors are based not on the perceived losses but on the perceived gains.
Survey Question:13	Assume that you bought 1000 shares of a company ABC for INR 12/share, expecting it to go up to INR 20/share in one year, based on its future growth plans. But within a month of your purchase, its price has fallen to INR 9/share. What would you do with the shares of ABC?
Answer Options	Hold on to all the 1000 shares because its price may recover

	Sell the shares immediately partly/fully to reduce/minimise the losses Buy more to reduce my average purchase price. Research the cause of the drop before any action even if could take some time
Coding the Answer Choice	Answer 1 or 3 – biased Answer 2 or 4 - unbiased

Bias Name (Group)	Self-Control Bias (Emotional)
Brief Explanation of the Bias	Self-control bias is a human behavioural tendency that causes people to consume today at the expense of saving for tomorrow. Self-control bias can also be described as a conflict between people's overarching desires and their inability, stemming from a lack of self-discipline, to act concretely in pursuit of those desires.
Survey Question:14	Suppose you have a budget of INR 4 lakhs for an international holiday with your family. Your holiday planning agency gives you 2 options to choose from: 1) An exotic European Cruise holiday listed at INR 7 lakhs but available to you at a special discounted price of INR 5 Lakhs. 2) A regular holiday plan in Europe to fit into your budget of INR 4 Lakhs. What option would you choose?
Answer Options	The exotic cruise holiday option even at a price above my budget because such good discounts may not be available again The regular holiday option because it fits my budget
Coding the Answer Choice	Answer 1 – biased Answer 2 – unbiased

Bias Name (Group)	Hindsight Bias (Emotional)
Brief Explanation of the Bias	Hindsight bias occurs when an investor believes that the happening of some event could have been predicted reasonably especially after it has already happened. But this belief can be dangerous as the investor can form cause and effect relationship between the two events even when the relationship may not be associated at all and thus resulting in irrational decisions.
Survey Question:15	Suppose you have been told by your friend about a stock that may give a 10% return on your investment within a month but with a risk of loss of 5%. What would you regret more?

Answer Options	Option 1: Buying the stock with the hope to get a 10% gains but ending up losing 5%. Option 2: Not buying the stocks with a fear of losing 5% but realizing after a month that stock price has gone up by 10% Option 3 : I would not regret in either options because my decision will be based on my risk tolerance
Coding the Answer Choice	Answer 1 or 2 - biased Answer 3 - unbiased

Bias Name (Group)	Over Confidence (Emotional)
Brief Explanation of the Bias	Overconfidence arises when individuals are overly optimistic about their trading abilities and believe their skills are sufficient for making sound investment decisions. Investors often correlate their performance with the overall market's high performance, overlooking that an excessive focus on their abilities, while neglecting other influencing factors, can lead to significant losses in the future.
Survey Question:16	Relative to other participants in the stock market, how good an analyst are you? (in terms of predicting the price movements in the Indian stock market)
Answer Options	Better than 50% of the people who invest in stock markets Average Worse than 50% of the people who invest in stock markets
Coding the Answer Choice	Answer 1 or 2- biased Answer 3 - unbiased

Source: Created by the author

The survey's cover note assured participants that their responses would be kept confidential and used exclusively for academic research purposes. Additionally, a statement highlighting the commitment to anonymity was included in the cover note (Appendix A), which indicated that respondents' choice to complete the survey implied their informed consent to participate without any objections.

Population and Sample for H3:

A convenience sampling approach, which evolved into snowball sampling, was employed to achieve the desired sample size of 100 + investor respondents for the study.

Considering the vast and diverse characteristics of the Indian stock market investor population, the primary objective was to work with sample data that minimised the margin of error (MoE).

Minimising the MoE increases the integrity and validity of the research findings. The MoE provides a quantitative measure of how much the insights derived from the sampled data may differ from the actual attributes of the larger population. A smaller MoE enhances the precision of the conclusions drawn from the research, allowing for more reliable predictions and actionable insights.

Invitations to complete the survey were initially sent to about 200 individual investors known to the researcher who had prior experience investing in the stock markets. Such targeted selection aimed to obtain a sample that accurately represented the experiences and perspectives of investors in the stock markets. Furthermore, the snowball technique was employed, where each invitee was asked to forward the survey in their circle of investors whom they deemed fit to participate in the survey. The methodology adopted for the study was expected to generate an acceptable margin of error (MoE).

Ultimately, the response yielded 139 usable surveys out of 153 completed responses, which necessitated the calculation of the margin of error, which was determined using an established formula.

$$\text{MoE} = Z \times \frac{\sqrt{p \times (1-p)}}{\sqrt{n}}$$

Where,

Z = Z-score (which is 1.96 for a confidence level of 95 %)

n = sample size

p = Estimated proportion of the population (substituted by 0.5 when the population is very large or unknown, to maximise variability).

= 1.96 × √ (0.5 × (1-0.5) ÷ 133

= 0.083

Therefore, the margin of error was calculated to be 8.3%.

Participant Selection for H3:

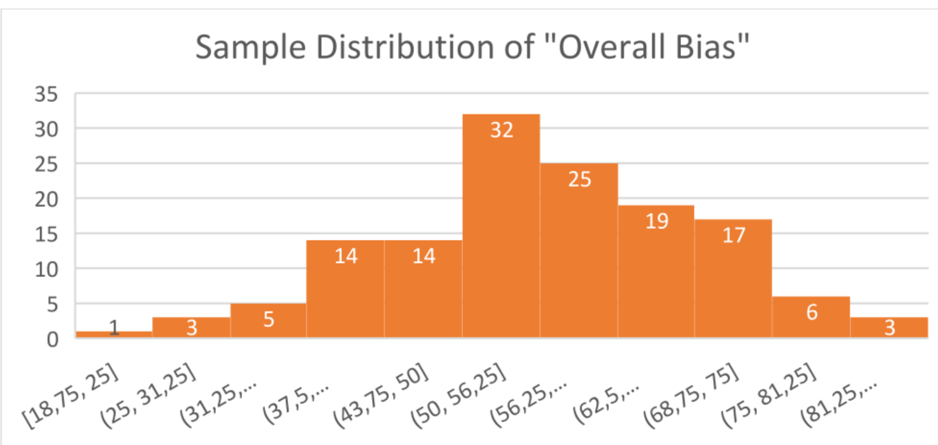
The initial participant list was carefully selected to encompass individuals from a diverse range of backgrounds and experiences, reflecting the researcher's extensive thirty-year career in the business sector. This diverse group included representatives from key financial areas such as banking, insurance, mutual funds, investment firms, and wealth management, as well as those from brokerage houses. In addition to these professionals, the list also featured entrepreneurs, who brought valuable insights from their ventures offering fresh perspectives.

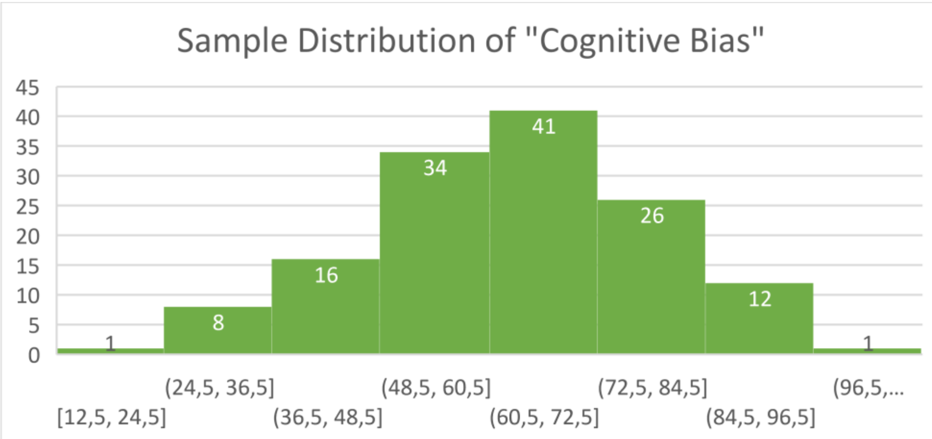
To further expand the participant pool, the researcher employed a snowball sampling technique. This approach encouraged existing participants to share the survey links with others who met the established criteria of exposure to investing in stock markets. This technique facilitates a broader reach and enhances the diversity of responses.

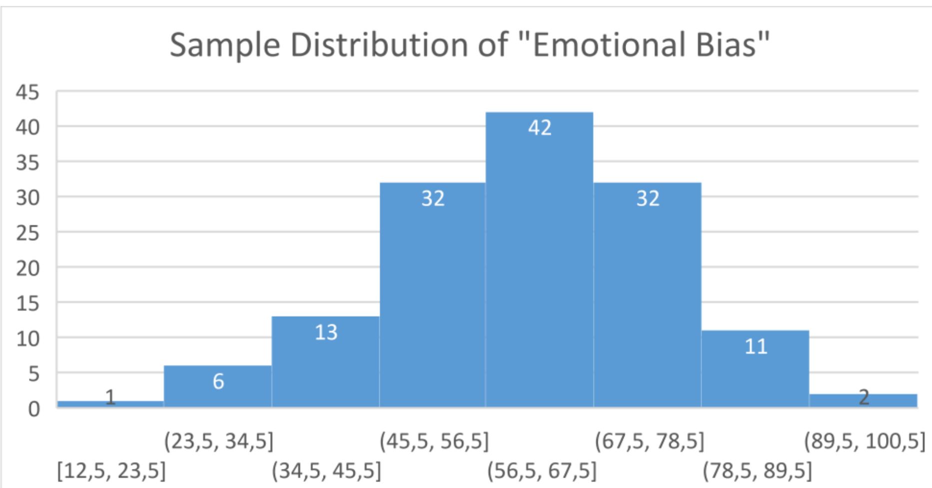
Ensuring a normal sample distribution is critical because many statistical methods rely on this assumption. A normal distribution enables researchers to apply various analytical techniques effectively, thereby enhancing the robustness and generalisability of their results. By focusing on these aspects, the research aims to provide a more transparent and more accurate understanding of investor behaviour and market dynamics in the Indian stock market.

Upon investigating the normality of the sample distribution of the group biases of sample investors recorded in the survey, a histogram distribution indicated that the sample satisfies the normality assumption, as shown in Figure 1.

Figure 1: Sample Distribution of “Overall”, “Cognitive” and “Emotional” Group Biases







Source: Created by the author

Additionally, the normality of the sample distribution of biases was evaluated using the Kolmogorov-Smirnov test, assuming that the null hypothesis is based on a normal distribution. The test yielded a p-value of 0.082 (Appendix D.1), which exceeds the significance threshold of 0.05. Consequently, the null hypothesis could not be rejected, and it could be concluded that the sample follows a normal distribution, making it appropriate for the t-tests conducted for H3.

The Central Limit Theorem (CLT), a fundamental statistical concept relevant to hypothesis testing, states that with a sufficiently large sample size (typically more than 30), the sampling distribution of the mean for a variable will approximate a normal distribution, regardless of the underlying distribution within the population. The applicability of the CLT encompasses almost all probability distributions, thereby justifying the use of t-tests with a sample size of 139 used for H3.

Data Collection and Instrumentation for H3:

The questionnaire and a link to the online survey were disseminated to selected participants primarily via WhatsApp messaging services and email. “Google Forms,” a robust, user-friendly and free online survey platform, was employed to facilitate participant survey completion on mobile devices or laptops. The Google Form survey options permitted respondents to edit their answers as often as they wished within the accessible period. It allowed them to navigate back and forth to attempt or edit their responses if needed.

The online survey was accessible for thirty days during May 2024, coinciding with the month when the elections were held in India during which the investors’ biases were expected to be at heightened levels. To improve the response rates, reminder messages were sent to non-respondents midway through this period, adhering to ethical considerations and avoiding spam. Compliance with established ethical standards for academic research, including those related to email spamming and participant privacy, was ensured throughout the study. These techniques facilitated a quicker turnaround in data collection and enhanced the overall response rate. By streamlining the process and eliminating potential biases, the researcher aimed to maintain the integrity of the content and ensure construct validity, thereby ensuring that the survey effectively measures what it intended to. Ultimately, the meticulous approach to data collection aimed to yield reliable and meaningful data.

After the survey completion window closed, 153 completed responses were recorded using Google Forms. The raw data were subsequently exported to MS Excel and R for the data wrangling process, which included discovery, structuring, cleaning, validation, and feature engineering to enhance the quality and integrity of the results.

By carefully considering both the normality of the sample distribution and the MoE, the research aimed to produce findings that accurately reflect the perspectives and behaviours of the broader investor population in the Indian stock market.

Overall, the rigour in the survey research methodologies adopted here contributed to the study's validity and reliability, which significantly contributed to the research objectives.

3.5 Data Analysis

Data Analysis of Hypothesis 1:

A two-sample t-test method was chosen for the hypothesis test (H1) as the most suitable approach for this analysis, primarily because it thoroughly accounts for key factors such as effect size, sample size, directional tendencies, and variability in the two quantitative datasets being compared statistically. The alternative hypothesis posited in this research asserts that the returns of the Indian stock markets experience a significant increase during the periods of Indian GEs when compared to non-election periods. This premise necessitated the application of directional (right-tailed) statistical tests, which are particularly apt for assessing hypotheses that predict a specific direction of change.

Given the extensive dataset of Indian annual stock market returns from 2000 to 2024, utilising NIFTRI data, leveraging software tools in R was exceptionally beneficial for executing the hypothesis test. R and R Studio's capabilities not only streamline the computational process but also enhance the reliability and robustness of the statistical inferences drawn from the test results. In this context, p-values and alpha values play a crucial role. The p-value represents the probability of obtaining an effect as significant as the one observed in the sample, assuming the null hypothesis is correct. The significance level, denoted by the symbol α (alpha), further clarifies the likelihood of making a Type 1 error when a true null hypothesis is incorrectly rejected. In practical terms, maintaining an alpha level of 5% means that there is a 5% risk of concluding that an effect exists when, in fact, it does not.

The p-values generated from the tests were scrutinised in analysing the research findings, yielding results notably lower than the established evidentiary threshold of 5%. Consequently, allowing for rejecting the null hypothesis in support of the alternative hypothesis H1, confirming the preliminary observations that stock market annual returns rise significantly during Indian GE years.

Data Analysis of Hypothesis 2:

To evaluate the second hypothesis (H2), the researcher employed a comparative analysis using two distinct datasets to assess their mean values. The first four datasets comprised quantitative measurements of market volatility (India VIX index daily closing value) for the month surrounding four Indian GE result dates in 2009, 2014, 2019, and 2024. These datasets were created to represent the alternative hypothesis H2.

In contrast, the second set of 3,864 datasets consisted of twenty-one trading days of IndiaVIX data points each, calculated on a daily rolling basis from August 2008 to May 2008. They represented the null hypothesis H0, which served as a baseline against which the election-related volatility could be statistically compared.

Therefore, the researcher applied a “Two-Sample t-test”, a statistical method designed to determine whether there is a significant difference between the means of two independent groups. Additionally, the researcher employed a directional statistical test method, which is well-suited for this analysis given the direction of the hypothesis. This choice of right-tailed test was particularly relevant, given that the alternative hypothesis suggested a substantial increase in volatility within the Indian stock market during the election periods compared to lower volatility in non-election periods. The results were analysed with a primary focus on the p-value in comparison to the significance level of 0.05. Through this approach, the study aimed to provide generalisation to the relationship between Indian GEs and high short-term stock market volatility.

Given the substantial amount of data processed in this analysis, the researcher found software tools in “R” particularly advantageous for conducting the statistical test, as the software is known for its robust statistical capabilities, facilitating efficient data manipulation and analysis, thereby enhancing the reliability of the results derived in this research.

Data Analysis of Hypothesis 3:

After the closure of the submission time window on 31st May, 2024, the raw survey data obtained from the Google Form were imported into a Microsoft Excel spreadsheet, which was necessary for data wrangling to enhance the reliability of the tests. During the wrangling process, initially, fourteen responses were excluded from the dataset because they did not meet the criterion of respondents' mandatory exposure to stock markets.

Subsequently, each of the first sixteen survey questions was systematically labelled with the prefix alphabet "C" for the cognitive bias category or "E" for the emotional bias category, followed by the specific name of the bias. This labelling technique facilitated simple and identifiable categorisation of investors' biases for further analysis.

Based on the respondents' answers, data was initially coded using a binary approach, recording "0" for the absence and "1" for the presence of each of the sixteen specific biases among investors. Six observations from the "Gender – Prefer not to answer" and "Occupation - Students" categories were omitted from the survey data samples due to their insufficient sample size and irrelevance in the demographic analysis. Feature engineering techniques were employed to re-code the factor levels in the demographic data, such as qualification, income and occupation of investors, to yield a more meaningful analysis supported by a sufficient sample size. Descriptive analysis visual tools in R, such as bar graphs and box plots, were used to analyse the investors' specific biases and group biases in relation to their demographic profile.

The binary-coded data from each of the specific biases of investors was aggregated and proportioned to construct an ordinal, continuous dataset for the group biases (Cognitive, Emotional, and Overall). The jittering technique was employed further to refine the distinct steps in the data distribution, enabling the assessment of sample data normality using the Kolmogorov-Smirnov test.

Statistical methods, including one-sample, right-tailed t-tests, were employed to test the investors' group biases using data analysis tool in Microsoft Excel.

The p-values for one-sample, right-tailed t-tests were computed using the"Descriptive Statistic" and "T-DIST" data analysis tool in the MS Excel, using the formula:

$p - value\ =\ 1\ -\ T.DIST\ (t, n - 1,1)$

Where,

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

$\bar{x}$ = the sample mean

μ = null mean,

s = standard deviation of the sample

n = sample size

The "Descriptive Statistics" tool in MS Excel was used to generate the sample mean, standard deviation, sample size, confidence level, and standard error of the sample data used for testing H3.

For chi-square tests and Cramer's V statistic, which are applied to categorical data, the proportioned values of group biases were recoded by converting all proportion values below 0.5 to "0", indicating an unbiased investor, and those at or above 0.5 to "1", denoting a biased investor. chi-square tests were conducted on the categorical data to determine any significant associations between group biases and the demographic profile of the investors. Further, the Cramer –V tests were conducted to get the strength of the association wherever the chi-square results established significant association (p-values < 0.05). Linear regression models (with and without interaction terms) were used to test significant correlation of investors' group biases with their demographic profiles. Interaction terms help capture the joint effect of two or more independent demographic variables on the dependent variables (biases). For example, a significant impact of age and gender may be established on investors' emotional bias, which may not be established when tested independently for age and gender.

3.6 Research Design Limitations

Hypothesis 1:

- NIFTY50 or NIFTRI is a benchmark index for the Indian stock market. It reflects the performance of the top fifty companies by market capitalisation across various sectors of the economy. Consequently, it provides a broad overview of India's economic performance rather than a precise measure of its financial health. In the early 1990s, India had only a few large companies representing a significant portion of the market. However, this is changing rapidly due to the remarkable growth of the Indian economy, which has led to a diminishing proportion of Nifty 50 companies in the overall stock market landscape.

- The dataset employed for hypothesis testing utilised an approximation technique that assumes an average of 250 trading days per year to represent the annual stock market returns during non-election periods. This may not precisely align with the number of days used to calculate the yearly stock market returns in the dataset of election years.

Hypothesis 2:

- Low liquidity in the options market, especially for long-dated options, can create biases in the calculations of IndiaVIX, potentially distorting the outcomes. Furthermore, the lack of transparency in displaying the calculation details of IndiaVIX data complicates accurate interpretation.
- The IndiaVIX is a volatility index derived from the Nifty options market. It is essential to acknowledge that the IndiaVIX may not fully encapsulate the volatility of the entire stock market. Since it is based explicitly on Nifty options, its representation is inherently limited to the dynamics and trading behaviours within that segment, potentially overlooking broader market volatility indicators that could arise from other asset classes or indices. This limitation suggests that while the IndiaVIX can provide insights into market sentiment and volatility expectations within the Nifty options, it should be considered alongside other measures to comprehensively understand overall market volatility if the research demands it.

Hypothesis 3:

- The observation regarding the representation of sample participants in studies of the Indian stock market highlights a crucial aspect of research methodologies in financial studies. It underscores the importance of understanding the diversity and demographics of investor profiles while assessing market behaviour and trends. When we consider the assumption that the sample accurately represents the broader population of the Indian stock market, it’s vital to recognise that the limited inclusion of foreign investors challenged the representation. Foreign investors often possess different investment strategies, risk tolerances, and market knowledge compared to domestic investors, which can skew the findings if they are underrepresented in the sample. Their behaviour can significantly impact market dynamics, especially in an increasingly globalised financial landscape. In contrast, domestic investors provide a more robust representation reflective of local market conditions. Their demographic characteristics—such as age, gender, income level, education, and trading experience—play a significant role in shaping investment preferences and market activity. In summary, while the underrepresentation of foreign investors poses challenges to generalising findings, the depth and diversity within domestic investor profiles can still provide valuable insights when understood thoroughly. It highlights the adequacy of the sampling methodologies that consider the broad spectrum of domestic participant demographics to capture the complexities of investor behaviour within the Indian stock market.
- While the study identifies sixteen key biases influencing individuals, these may not encompass the full range of emotional and cognitive factors affecting investors' decisions. The statement points out a potential limitation in the research regarding investor behaviour,

specifically in how biases are represented. Human biases can be quite complex, and different contexts can lead to varying influences on their behaviour. For instance, factors such as market volatility, personal financial situations, or even broader economic conditions can elicit emotional reactions that aren't fully captured by the predefined biases. Personal experiences, cultural background, and psychological traits can also lead to unique variations in how investors respond to similar situations. By relying solely on the sixteen independent biases, there is a risk of oversimplifying the intricate web of influences that shape decision-making. Investors may experience a combination of multiple biases simultaneously or may be influenced by biases not accounted for in the research framework. This gap highlights the necessity for a more comprehensive understanding of the physiological and psychological landscape in which investors operate, suggesting that future studies should consider a wider array of factors to provide a more holistic view of investor behaviour affecting the financial markets.

3.7 Conclusion

The research employed a quantitative approach to examine the hypotheses within the context of the Indian stock markets during the Indian General Elections, a period marked by significant market activity and shifts in investor sentiment. This approach was closely aligned with various Behavioural Financial theories that explore the cognitive and emotional influences on investor behaviour.

The empirical evidence gathered from the Indian stock market during these elections presents a compelling challenge to the foundational assumptions of classical financial theories.

These theories assert that investors act as rational decision-makers, concluding that markets should efficiently reflect all available information, thus minimising mispricing. However, the findings from this study suggest otherwise, establishing that cognitive and emotional biases play a crucial role in investor behaviour during Indian GEs, which cause stock market volatility in the short term and abnormal returns in the medium term.

To structure the research hypothesis testing effectively, the central hypothesis (H) was divided into three sub-hypotheses: H1, H2, and H3. The first two hypotheses, H1 and H2, were explicitly stated to clarify the first research question: Do the Indian stock markets diverge from their intrinsic pricing behaviour during periods of political uncertainty, such as during the GEs in India?

The hypothesis tests on H1 and H2 relied on historical secondary data of NIFTRI and IndiaVIX, spanning from 2000 to 2024, within the Indian stock markets, allowing for a detailed statistical comparison of election period datasets with non-election period datasets.

In contrast, H3 was investigated using primary survey data that focused on effectively capturing investors' financial biases, aiming to answer the second research question: Do investors exhibit financial biases in their decision-making processes, which lead to mispricing in the stock markets?

This survey was primarily designed to capture the emotional and cognitive biases of investors that influence financial decision-making during the 2024 Indian general election, offering a unique and in-depth understanding of investor behaviour in the current political climate. The rigorous survey research methodologies employed contributed to the study's validity and reliability. Sample data from the survey was found to be normally distributed and within acceptable margins of error, which justified the use of one-sample, right-tailed t-tests for hypothesis testing. This statistical approach allowed the researchers to draw conclusions about the generalisability of investors' biased nature, suggesting it as a contributing factor to abnormal market behaviour during the Indian general elections.

Moreover, the demographic information collected through the survey provided additional layers of analysis, which, although not directly instrumental in testing the central research hypothesis, offered valuable insights into the diverse factors affecting investor behaviour. These insights can significantly enhance the understanding of market dynamics, paving the way for future explorations in the realm of BF and setting a foundation for further inquiries into how psychological biases can influence market efficiency and investor decisions in uncertain times and situations.

CHAPTER IV:

RESULTS

The research hypothesis posits that the occurrence of GE in India triggers significant volatility and abnormal returns in its stock markets in the short and medium terms, due to investors' biases.

To conduct the research effectively, the central research hypothesis (H) was tested for its three sub-hypotheses—H1, H2, and H3 — against their respective null hypotheses (H0).

4.1 Results for Hypothesis H1

H1: The stock markets in India exhibit abnormally high positive returns during the year surrounding their general elections, significantly exceeding the annual returns observed during non-election periods.

H0: There were no significant abnormal market returns during the Indian GE years.

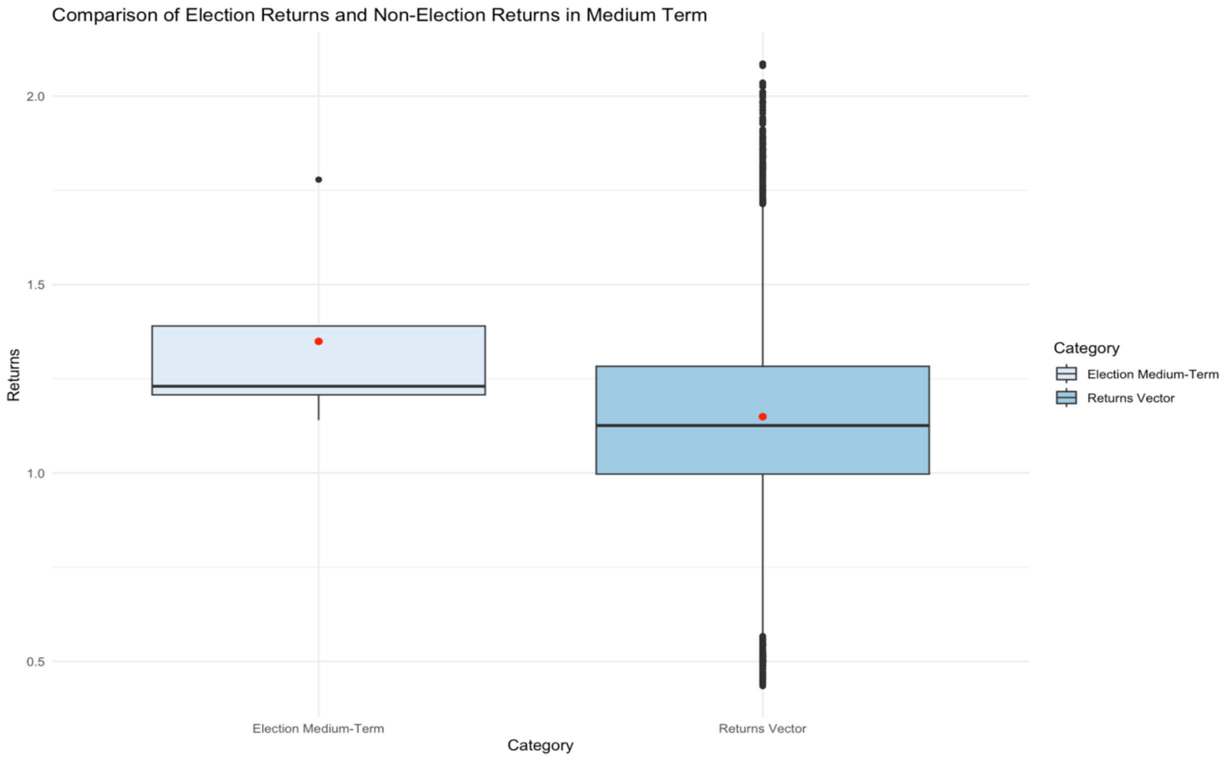
Table 3: Annual Returns of NIFTRI during GEs (2004 to 2024)

General Election Year	Annual Market Returns (% age)
2004	20.73
2009	77.83
2014	39.06
2019	14.16
2024	23.35

Source: created by the author

The mean of annual return for the five GE years representing the alternate hypothesis (H1) = 35.1%, whereas the mean of annual returns for non-election periods representing the null hypothesis H0 = 14.92% . (Appendix B.3 Code for Hypothesis Testing using t-test in “R”).

Figure 2: Annual Returns of NIFTRI during GE and non-GE periods from 2000 to 2024 using Box Plots



Source: Created by the author

Table 3 and Figure 2 demonstrate that the average 1-year return in the Indian stock market during general election years is abnormally higher than that during non-election periods.

Inferential results from "Student's two-sample t-tests" using "R" (Appendix C.3 Code for Hypothesis Testing using t-test in "R") generated the following results:

- T value = 1.765, indicating a significant effect size, given the data sets' standard deviation and large sample size.
- df = 4992, which denotes the degree of freedom which is related to the sample size.

- The 95% confidence interval = (0.0138, infinity) indicates that, at a 95% confidence level, the difference in means of the annual returns between GE years and non-GE years is at least 1.38% in general.

- The p-value of 0.03881 denotes the probability that the null hypothesis is valid if it is rejected is 3.88%. Therefore, for a significance level (**α**) of 0.05, p-value < α. Hence**,** H0 is rejected in favour of H1.

4.2 Results for Hypothesis H2

H2: The Indian stock market exhibits significantly elevated volatility during the month surrounding the announcement of the general election results, surpassing the volatility observed during other short-term periods.

H0: There is no abnormal volatility in the Indian stock markets during the short, one-month period around the GE results dates.

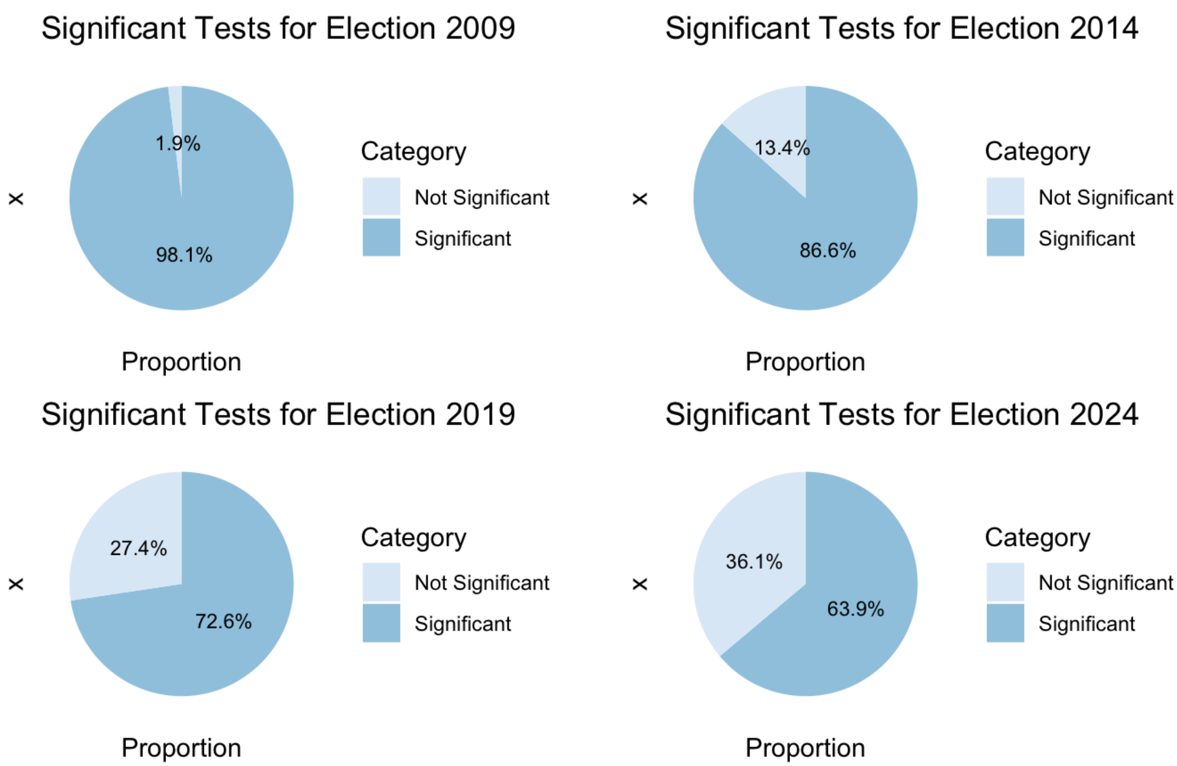
Test results for short-term market volatility using a "two-sample, directional right-tailed t-test' using "R":

Table 4: Proportion of Significant p-values during Indian GEs 2009 to 2024

Indian GE year	**Proportion of Significant p-values (in %)**
2009	98.08
2014	86.6
2019	72.64
2024	63.87

Source: Created by the author

Figure 3: Proportion of Significant p-values during Indian GEs from 2009 to 2024 using Pie Charts



Source: Created by the author

The results of the short-term volatility tests in H2, as depicted in Table 4 and Figure 3, states the proportion of statistically significant p-values (<0.05) during the GEs in India. By interpreting the results, it can be established that the volatility of Indian stock markets during the one-month period surrounding the 2009 election was significantly higher, 98.084% of the time, compared to the market volatility for similar short periods during non-election times. Similarly, the proportion of significant results for the years 2014, 2019 and 2024 yeilded values of 88.6%, 72.6% and 63.9% respectively.

While each GE year displays a large proportion of significant results, it may be prudent to consider the potential for misleading correlations between elections and market volatility, as various other factors may also have influenced the outcomes of each general election year. This effect can be mitigated by averaging the proportion of significant test results across the four general election years, calculated as follows: (Sum of 98.08, 88.38, 72.64, and 63.87) ÷ 4 = 80.75%. This represents a high proportion of significance by average.

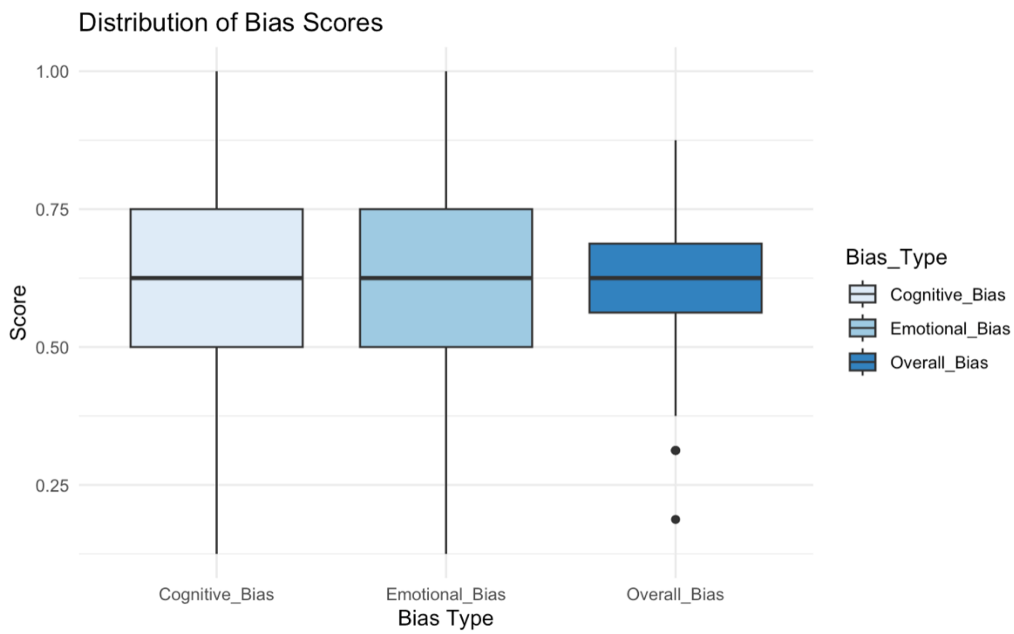
Therefore, H0 can be safely rejected in favour of H2.

4.3 Results for Hypothesis H3

- H3: Financial biases in investors cause the abnormal market behaviour during Indian GEs.

H0: Investors are rational in their decision-making and do not succumb to emotional and cognitive biases in their financial decision-making.

Figure 4: Descriptive Result of Group Bias Scores using Box Plots



Source: Created by the author

The initial analysis of the box plot in Figure 5, which depicts the survey data on investors, suggests that a significant majority, exceeding 50% of investors, display cognitive and emotional biases, collectively leading to overall biased decision-making traits among investors. These observations contradict the assumptions in traditional financial theories that investors in stock markets are rational decision makers. Thus, the stock markets are always intrinsically priced.

A series of statistical tests was conducted on survey data to further substantiate these observations. The tests aimed to determine whether investor biases, grouped under cognitive, emotional, and overall categories, are prevalent in the sample and within the broader population. The analyses provide a broader understanding of the impact of biases and help identify patterns that influence investor behaviour in their financial decisions during times of uncertainty.

The results of the hypothesis tests for H3, conducted across the three categories of bias data—"Overall," "Cognitive," and "Emotional"—yielded descriptive output values, including the mean, standard deviation, sample size, and confidence interval, using the "descriptive analysis" tool in MS Excel. These outputs served as the basis for the statistical t-tests, which were used to arrive at the p-values of the tests.

Table 5: Descriptive and Statistical Results of "Overall Bias" in Investors

Overall Bias	**Descriptive Results**
Mean ($\bar{x}$)	59.757 (%)
Standard Error	1.0870
Median	62.5
Mode	56.25
Standard Deviation (s)	12.8157
Sample Variance	164.2409
Kurtosis	0.07262
Skewness	-0.2348
Range	68.75
Minimum	18.75
Maximum	87.5
Sum	8306.25
Count (n)	139
Confidence Interval (@ 95.0%) (Ci)	2.149347

Source: Created by the author

Statistical results of p-value and confidence intervals using the descriptive results:

Step 1: Calculate the t value,

where t denotes signal-to-noise ratio

$(\bar{x} - \mu)$ represents the signal (effect size) and

$(\frac{s}{\sqrt{n}})$ represents the noise (standard error of the mean)

$\bar{x}$ = the mean value of the overall bias

μ = the mean value of the Null hypothesis (which is 0 in this case),

s = standard deviation of the sample data

n = sample size

Hence,

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

= 59.75719 ÷ 1.087009

= 54.974

Step 2: Calculate the p-value using the “t-dist” tool in MS Excel

where t-dist is a data analysis tool in MS Excel, which requires inputs “t” and “n” as:

$$t - dist\ (t, (n-1), 1) \ = \ 1.0000$$

p-value = 1- (t-dist)

= (1-1.0000)

= 0.0000

Therefore, for significance value (α) = 0.05, p-value is < α.

CI = (lower estimate, upper estimate), a range that likely contains the unknown value of the population.

= ($\bar{x}$ - Ci, $\bar{x}$ + Ci)

where,

$\bar{x}$ = sample mean = 59.75

Ci = 2.15

CI = (59.75 - 2.15, 59.75 + 2.15)

= (57.60, 61.90).

Consequently, it can be inferred with 95% confidence that the mean of the "overall bias" observed among investors in the sample is expected to be between 57.60% and 61.90% of the population.

Table 6: Descriptive and Statistical Results of "Cognitive Bias" in Investors

Cognitive biases	**Descriptive Results**
$\bar{x}$ = Mean	58.813 (%)
Standard Error	1.446607
Median	62.5
Mode	62.5
s= Standard Deviation	17.05525
Sample Variance	290.8814
Kurtosis	-0.2611
Skewness	-0.17974
Range	87.5
Minimum	12.5
Maximum	100
Sum	8175
n = Count	139
Ci = Confidence Level(95.0%)	2.860381

Source:Created by the author

Statistical results of p-value and confidence interval using the descriptive results:

Step 1: Calculate the t value using the formula:

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

where,

$\bar{x}$ is the mean value of the cognitive bias = 58.8126

μ is the mean value of the Null hypothesis = 0

s is the Standard Deviation of the data = 17.0553

n is the sample size = 139

Therefore,

t = 40.65579

Step 2 is to calculate the p-value using the formula p-value = (1- t-dist)

where t-dist is a statistical tool in MS Excel

t-dist(t, (n-1), 1) =1.0000

p-value = (1-1.0000)

= 0.0000

Therefore, for asignificance value (α) = 0.05, p-value < α.

The results from the descriptive analysis in Table 6 show that the confidence interval (CI) at 95% is 2.86 and the sample mean of cognitive bias in investors is 58.81.

CI can be thus be calculated as: $(\bar{x} - Ci, \bar{x} + Ci)$

= (58.81 - 2.86, 58.81 + 2.86)

= (55.95, 61.67)

Consequently, it can be inferred with 95% confidence that the cognitive biases observed among the sample investors are expected to be in the range of 55.95% to 61.67% of the population.

Table 7: Descriptive and Statistical Results of "Emotional Bias" in Investors

Emotional biases	**Descriptive Results**
$\bar{x}$ = Mean	60.7014 (%)
Standard Error	1.41304
Median	62.5
Mode	62.5
S = Standard Deviation	16.6595
Sample Variance	277.5388
Kurtosis	-0.00923
Skewness	-0.25398
Range	87.5
Minimum	12.5
Maximum	100
Sum	8437.5
N = Count	139
Ci = Confidence Level(95.0%)	2.794009

Source: Created by the author

Statistical results of p-values and confidence intervals using the descriptive results:

Step 1: Calculate the t value using the formula:

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

where,

$\bar{x}$ is the mean value of the emotional bias = 60.7014

μ is the mean value of the Null hypothesis = 0

s is the Standard Deviation of the data = 16.66

n is the sample size = 139

Therefore t = 42.95804

Step 2 is to calculate the p-value using the formula p-value = (1- t-dist)

where t-dist is a tool in MS Excel

t-dist(t, (n-1), 1) = 1.0000

p-value is = (1-1.0000)

= 0.0000

Therefore for a significance value (α) = 0.05, p-value is $< \alpha$

At 95% confidence level, Ci = 2.79

Therefore, CI = $(\bar{x} - Ci, \bar{x} + Ci)$

= (60.7 - 2.79, 60.7 + 2.79)

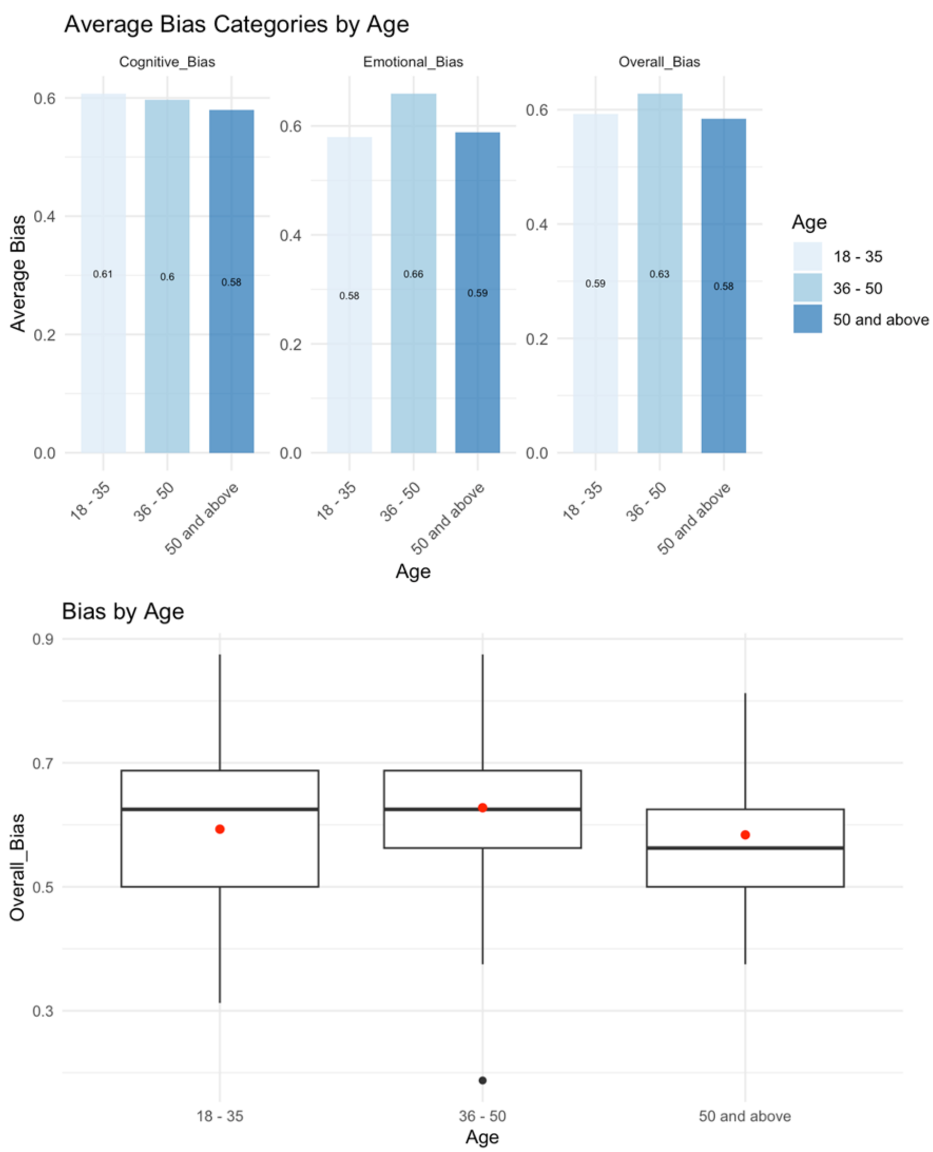
= (57.91, 63.49)

Hence, we can interpret the results with 95% confidence that emotional bias ranges from 57.91% to 63.49% of the investor population.

4.4 Demographic Analysis of Investors' Biases

Descriptive Analysis using Bar Plots and Box Plots

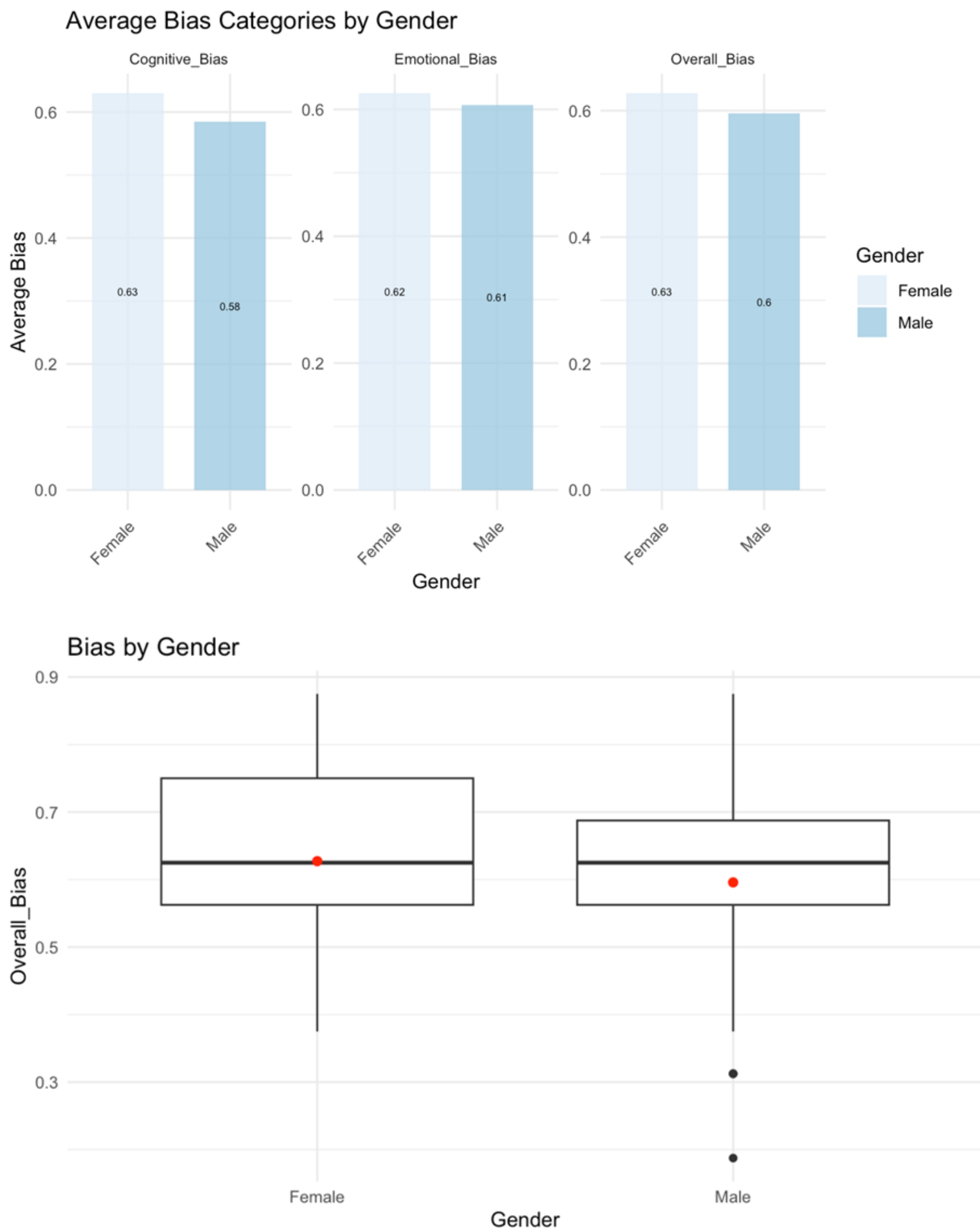
Figure 5: Analysis of Group Biases by Age



Source: Created by the author

- The age group 36 to 50 appear most biased, more so, emotionally.

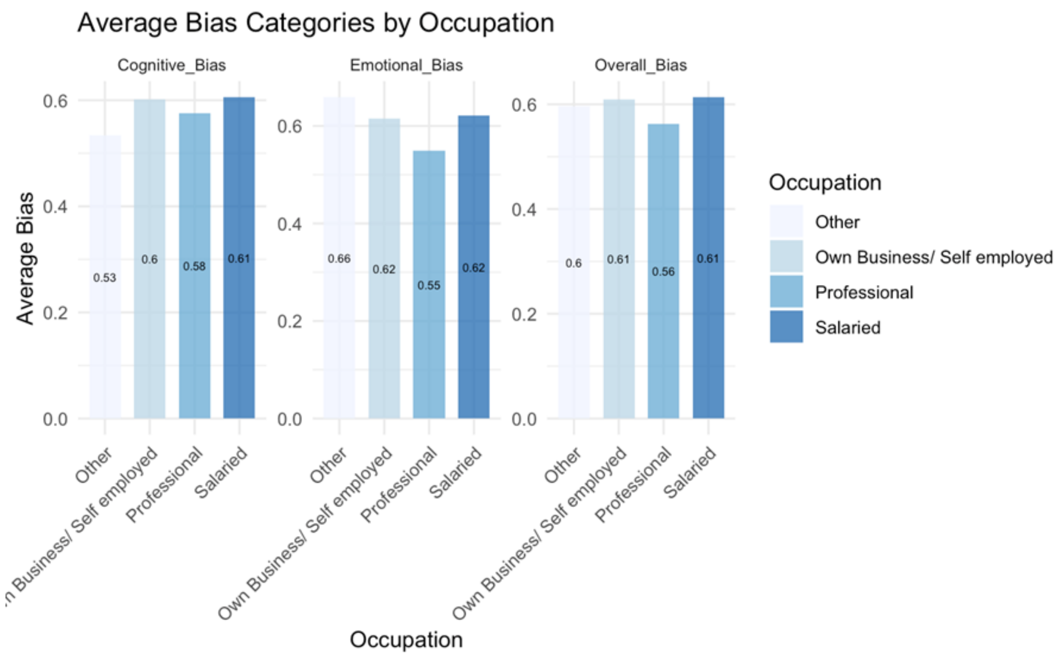
Figure 6: Analysis of Group Biases by Gender

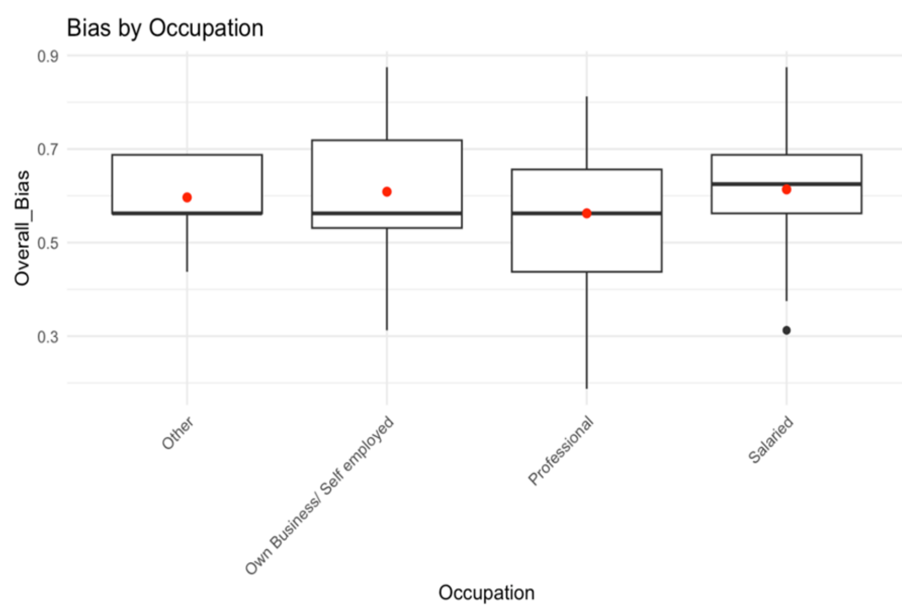


Source: Created by the author

- Female investors appear more biased in all group biases than men.

Figure 7: Analysis of Group Biases by Occupation



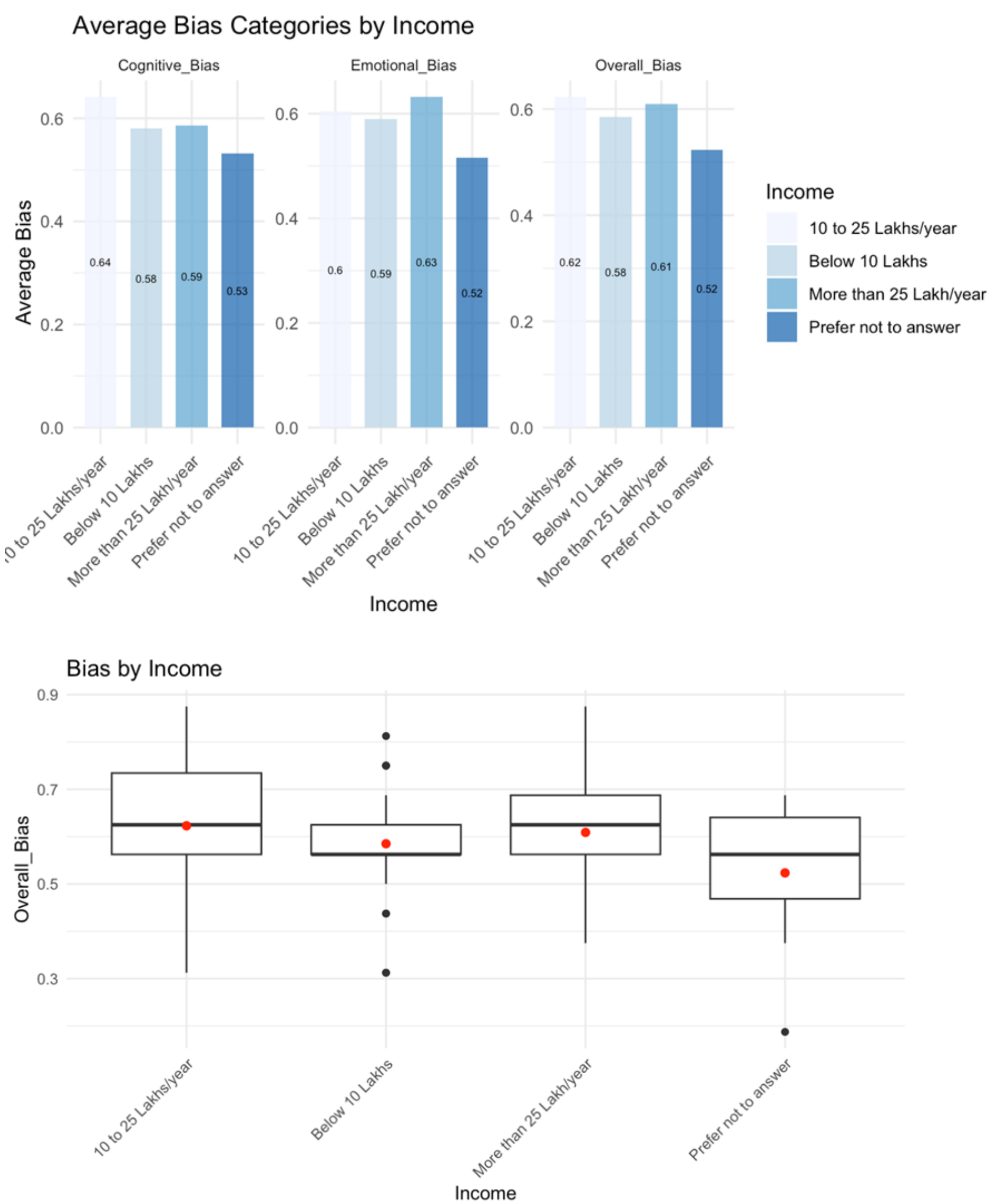


Source: Created by the author

- Professionals appear to be less biased than others, especially emotionally.

- Business owners appear more biased than other occupation categories.

Figure 8: Analysis of Group Biases by Income

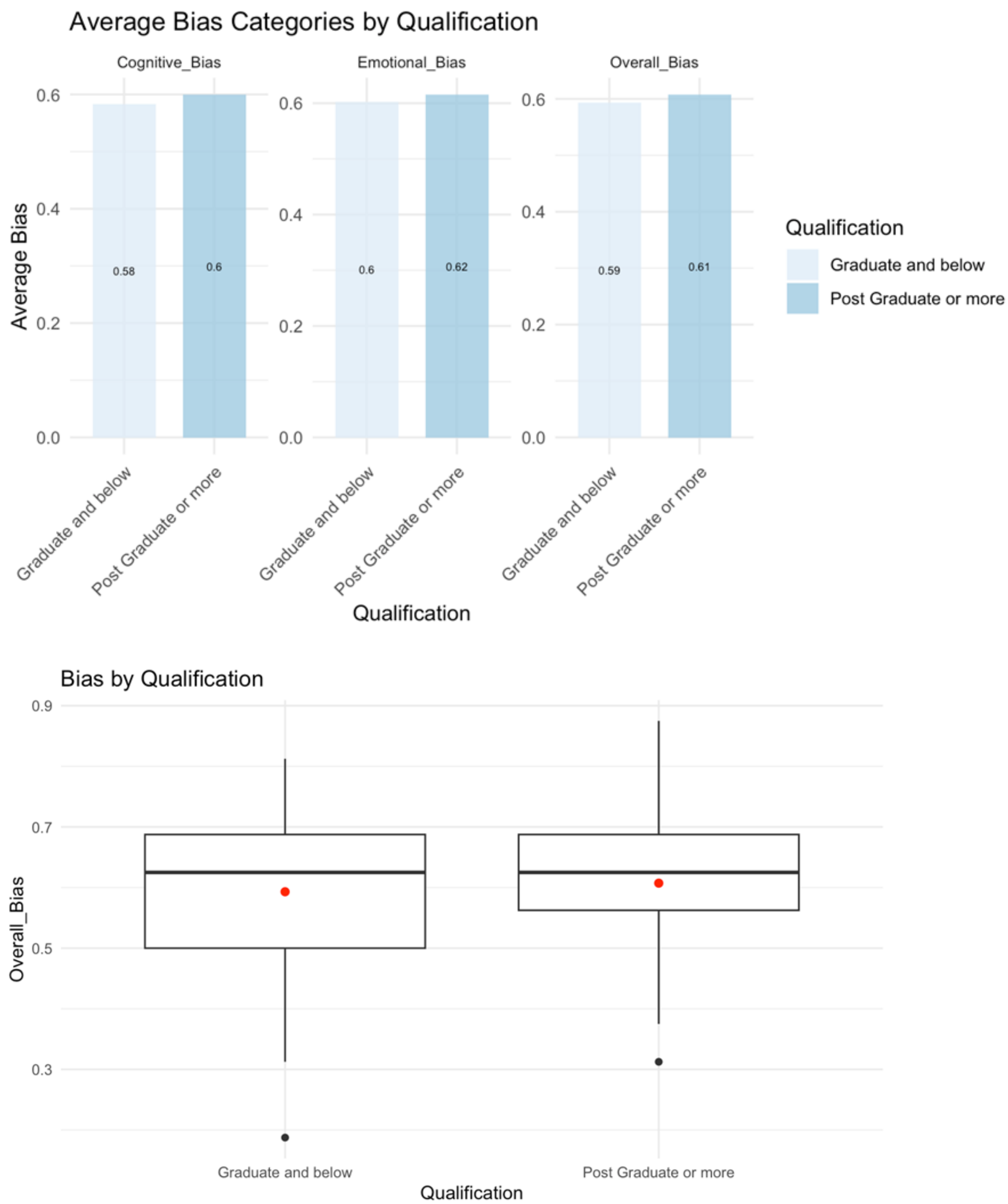


Source: Created by the author

- Investors with income levels between 10 to 25 lakhs tend to be more biased than others.

- Investors who do not prefer to disclose their income levels are less biased than others.

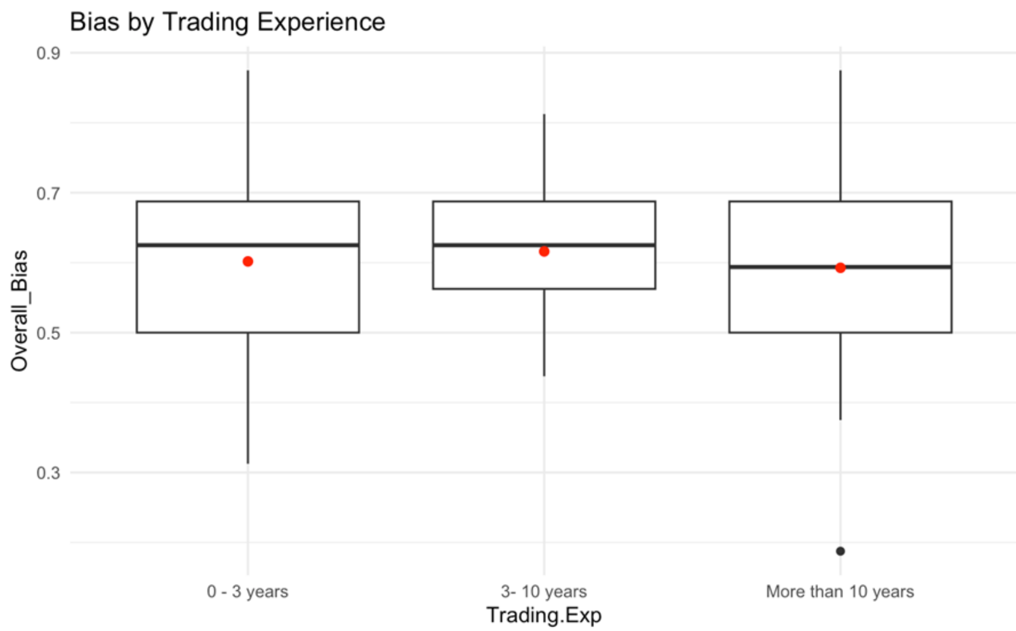
Figure 9: Analysis of Group Biases by Qualification



Source: Created by the author

- Investors who are Post Graduate and above tend to be more biased than Graduates and below.

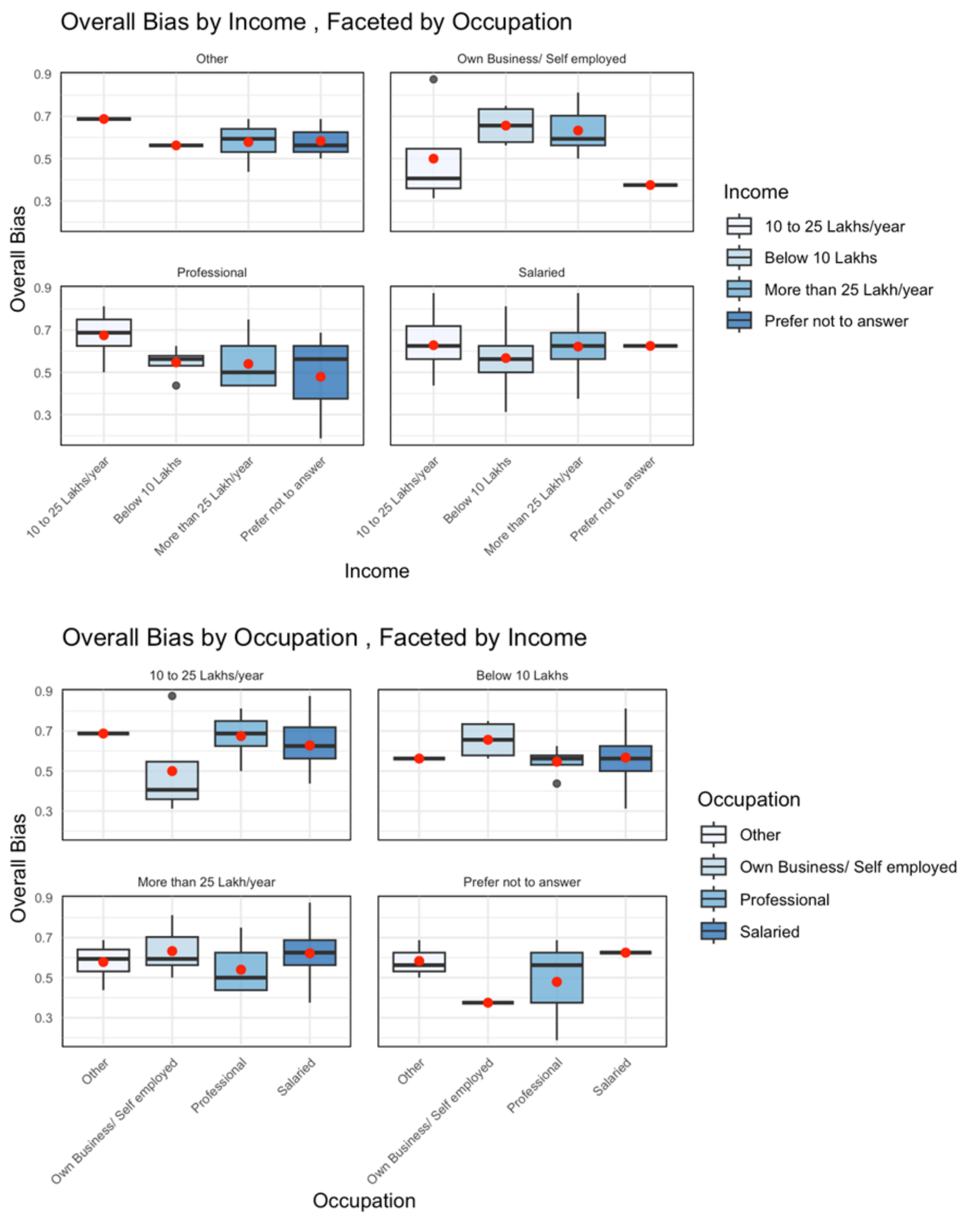
Figure 10: Analysis of Overall Bias by Trading Experience



Source: Created by the author

- Investors with more than 10 years of trading experience appear less biased than those with less experience.

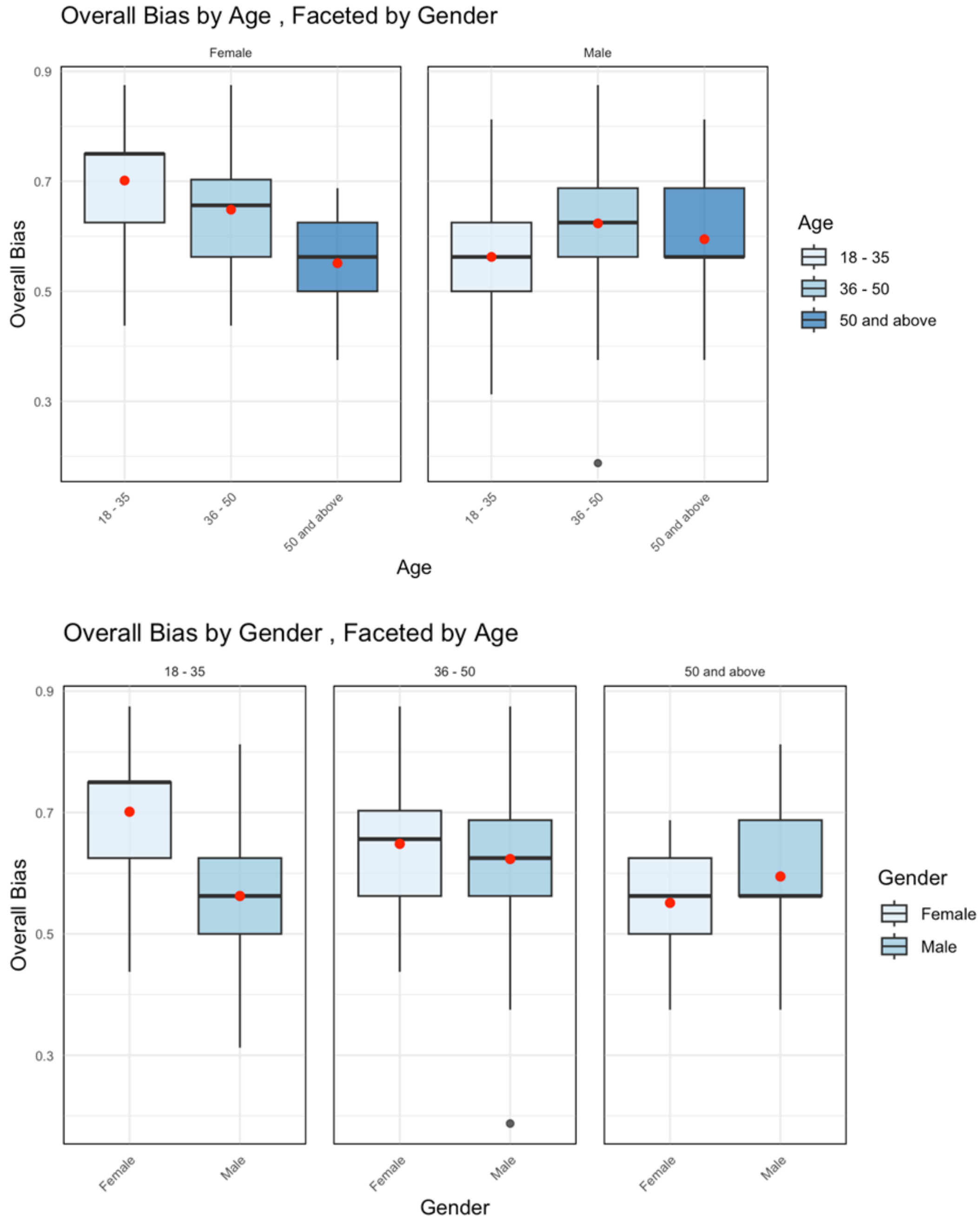
Figure 11: Analysis of Overall Bias by Occupation and Income



Source: Created by the author

- Investors earning an income of more than ₹ 25 lakhs appear to have a similar level of overall bias, irrespective of their occupation.

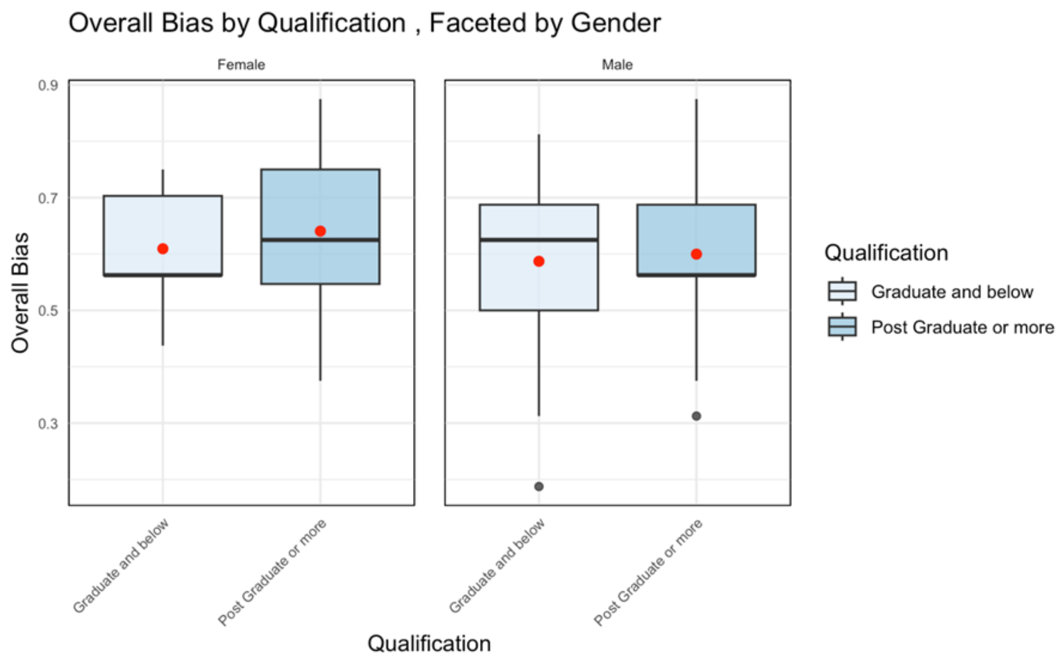
Figure 12: Analysis of Overall Bias by Gender and Age



Source: Created by the author

- It appears that overall bias in female gender tend to decrease as they age.

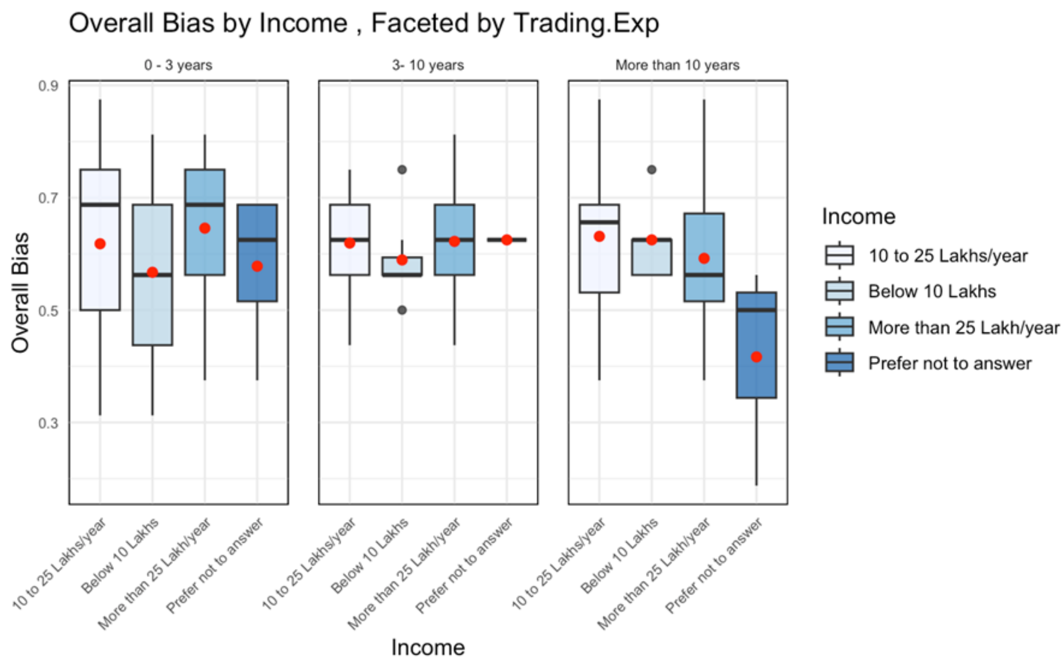
Figure 13: Analysis of Overall Bias by Qualification and Gender



Source: Created by the author

- With higher educational qualifications, both genders appear to become more biased.

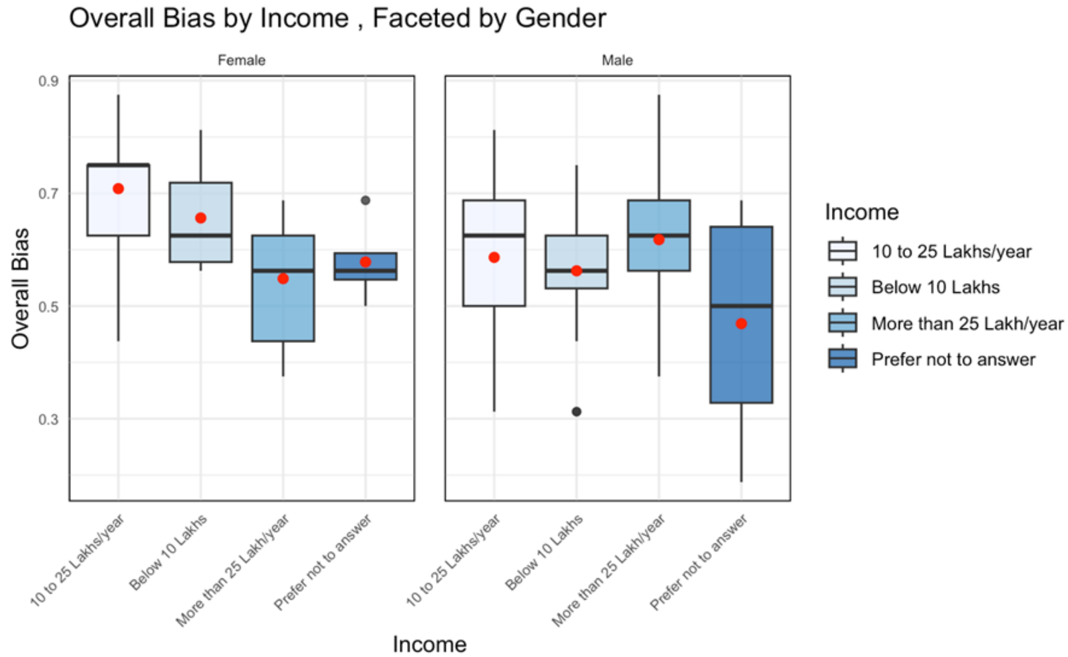
Figure 14: Analysis of Overall Bias by Income and Trading Experience



Source: Created by the author

- Highly experienced Investors who do not prefer to disclose their income range tend to be less biased.

Figure 15: Analysis of Overall Bias by Income and Gender



Source: Created by the author

- Male Investors who do not prefer to disclose their income range tend to be less biased.

- Female Investors tend to reduce their Overall bias as they earn more.

Figure 16: Analysis of Overall Bias by Occupation and Age

Source: Created by the author

- Younger Investors in the 18-35 age group appear to be more biased when they have a fixed income from salaries than professionals and business owners.
- Business Owners in the 36-50 age group appear to be the most biased.

Statistical Results of Investors' Biases with their Demographic Profiles:

Table 8: Chi-Square and Cramer's V Tests of Significant Association and Strength

Bias Category	Individual Bias	Demographic profile	p-values (<0.05)	Cramer's V coefficient
Cognitive	Gambler's fallacy	Age	0.0485	0.213
Cognitive	Recency	Age	0.0026	0.299
Cognitive	Recency	Income	0.0105	0.291
Cognitive	Over Optimism	Age	0.0295	0.23
Cognitive	Over Optimism	Trading Experience	0.0048	0.284
Cognitive	Representativeness	Age	0.0004	0.341
Cognitive	Representativeness	Occupation	0.0325	0.257
Cognitive	Representativeness	Income	0.0052	0.310
Emotional	Status quo	Occupation	0.0204	0.271
Emotional	Herd	Trading Experience	0.0265	0.234
Emotional	Disposition Effect	Qualification	0.0383	0.196
Emotional	Self-Control	Income	0.0062	0.305
Emotional	Hindsight	Age	0.0493	0.213
Emotional	Hindsight	Income	0.0403	0.250

Source: Created by the author

From table 8, while the p-values of less than 0.05 qualify the association between the bias and the demographic profile as statistically significant, Cramer's V coefficient shows the strength of the association.

- Within the cognitive biases of investors, a strong association can be established between the "Representativeness Bias" and the profiles of investors in terms of "age", "occupation", and "income", among other significant associations.
- Within the emotional biases, the bias of "self-control" has high impact on investors.

Table 9: Significant Linear Regression Results of Group Biases (without Interaction)

Bias Category	Demography Profile	Demography groups	Estimate	Std. Error	t value	Pr>t
Emotional	Age	36-50	0.09023	0.04291	2.103	0.0376
Emotional	Occupation	Professional	-0.1368	0.0617	-2.218	0.0284
Overall	Income	Prefer Not to Answer	-0.1117	0.535	-2.088	0.0389

Source: Created by the author

Linear Regression of group biases run against demographical variables (without interaction terms) revealed statistically significant correlations (ceteris paribus):

- The age group 36-50 has a positive effect on emotional bias levels in investors.
- The occupations of professionals have an inverse effect on the emotional level of investors.
- Investors who prefer not to disclose their income have an inverse impact on their overall bias levels.
- No significant correlation was observed between any cognitive biases and the demographic profile of investors.

Table 10: Significant Linear Regression Results of Overall Bias (with interactions)

Demographic Profile	Interaction Profile	Demography groups	Estimate	Std. Error	t value	Pr>t
Age	Age	50+	-.2445	0.0883	-2.769	0.0066
Occupation	Occupation	Own Business	-.2411	0.1121	-2.151	0.0338
Gender	Age	Male: 50+	0.216551	0.092835	2.333	0.0216
Occupation	Income	Own Business & Self-employed : <10 Lakhs/year	0.3689	0.1539	2.397	0.0184
Occupation	Income	Own Business & Self-employed : >25 lakhs/year	0.2823	0.1308	2.158	0.0333

Source: Created by the author

Linear regression on investors' data with interactions between the demographic profiles categories and "Overall bias" of investors highlights some significant correlations:

- A positive correlation exists among the age category of all investors aged 50 and above. Still, a negative impact is observed in the age group of 50+ male investors on the overall bias of investors.
- Business Owners positively correlate with the overall bias if they have an annual income of less than ₹10 lakhs or more than ₹25 lakhs.

Table 11: Significant Linear Regression Results for Cognitive Bias (with Interactions)

Demographic Profile	Interaction Profile	Demography group	Estimate	Std. Error	t value	Pr>t
Age		50+	-0.3459	0.1248	-2.772	0.0066
Gender	Age	Male:50+	0.3158	0.1311	2.407	0.0178
Occupation	Income	Own Business & Self Employed : <10Lakhs/Year	0.5165	0.2174	2.376	0.0194

Source: Created by the author

- Investors aged 50 and above are more susceptible to cognitive bias. But a positive correlation is established if they are males.
- Self-employed and business owners have a strong correlation with their cognitive bias.

Linear Regressions on demographic profiles of investors with Emotional Biases (with interactions) produced no significant correlation.

4.4 Conclusion of the Results

The study's central hypothesis (H) posits that GEs in India have a significant impact on stock market volatility, leading to abnormal returns in the short and medium terms, primarily due to investor biases. The study was divided into three sub-hypotheses—H1, H2, and H3—to effectively test the central hypothesis.

For the analysis of H1 and H2, statistical tools within the software “R” were employed, allowing for rigorous data examination using statistical methodologies. In contrast, H3 was evaluated using descriptive and statistical techniques utilising “MS Excel” tools, which provided an additional approach to understanding the relationships at play.

The findings from the hypothesis tests for H1 and H2, conducted using two-sample right-tailed t-tests, statistically favoured the presence of abnormal stock market returns and increased volatility during GE compared to periods without elections. This confirms the hypothesis that political events significantly sway away from the intrinsic pricing of the stocks.

The statistical results of the hypothesis tests of H3, conducted individually on all three group biases of investors – Overall, Cognitive and Emotional yielded p-values below the significance level of 0.05. Further, the results of the confidence intervals for the three group biases established that even the lower values of the confidence interval were significantly above the null hypothesis value of zero. Therefore, the null hypothesis (H0) was rejected in favour of the alternative hypothesis (H3).

Initially, a descriptive analysis of the demographic profiles of investors revealed some interesting insights into potential associations between investor bias and their demographic characteristics. Further statistical tests conducted on the survey data using chi-square, Cramer V and linear regressions using the R tools, revealed significant association and correlation between financial biases and demographic profiles of investors, which is summarised as:

There is a significant association between the "representativeness bias" among investors and factors such as age, occupation, and income. The emotional bias of self-control notably influences investors, particularly those aged 36 to 50, who tend to exhibit higher levels of this bias. Professional occupations generally have a diminishing effect on emotional levels, while a reluctance to disclose income negatively affects overall bias. No significant correlations have been found between cognitive biases and demographic characteristics. Investors aged 50 and above show a positive correlation overall, although this group, particularly males, demonstrates a negative impact. Business owners with annual incomes below ₹10 lakhs or above ₹25 lakhs also display a positive correlation with bias. Furthermore, individuals aged 50 and above are generally more susceptible to cognitive bias, particularly males. Additionally, self-employed individuals and business owners demonstrate a strong association with bias.

CHAPTER V:

DISCUSSION

5.1 Discussion of Research Question One

Do the Indian stock markets diverge from their intrinsic pricing during periods of political uncertainty, such as during the GE in India, as outlined by traditional financial theories?

The statistical test results for hypotheses H1 and H2 effectively addressed the first research question. Periods surrounding GE often induce behavioural biases in individuals, leading to irrational decision-making in financial matters. This phenomenon results in short-term fluctuations in stock markets, consequently aligning with the broader fundamental factors of the economy.

The mid-term pricing behaviour of markets after the short period of high volatility during the Indian GE revealed a shift in investors' biases from a sentiment of pessimism to a mood of optimism. One can draw a parallel to the explanation offered by Pearce and Roley (1984), who suggest that markets tend to correct themselves approximately six months before an anticipated negative economic period (Pearce & Roley, 1984). The cautious approach among investors and businesses often delays new investment decisions before elections, only to resume once uncertainty recedes after the general election results. Fluctuations are a regular feature of the market, but they can become particularly concerning for investors when they escalate irrationally. During the brief period surrounding the announcement of election results, market price estimates can vary significantly, driven by biased assumptions that heighten volatility. The highest levels of political uncertainty are typically observed just before the election results are announced, a trend reflected by the IndiaVIX fear gauge. However, once the election concludes and concerns about potentially adverse outcomes from the new government's policies diminish, investments flow back into the economy. This rationality allows markets to realign their investment strategies based on the country's fundamental economic factors. Given the robustness of India's political and economic framework, a notable recovery in market returns is typically observed in the months following the general election results, regardless of which government or alliance is in power.

India's multi-party system has witnessed various government formations since 2004, with key elections including:

- 2004: The Congress party returned to power after defeating the BJP, with Dr. Manmohan Singh serving as Prime Minister.
- 2009: The UPA, led by Dr. Manmohan Singh, secured an even more significant majority amidst a massive electorate.
- 2014: These elections marked a significant shift in political power dynamics.
- 2019: The BJP won decisively, riding on the popularity of the Modi wave.
- 2024: The BJP secured a third consecutive victory with the support of its allies.

Despite navigating a range of political scenarios throughout these elections, the Indian stock markets have consistently exhibited a compounded average growth rate of 14.92% (as measured by the NIFTRI index) from 2000 to 2024. As the largest democracy in the world, India’s governance structure is established through a democratic electoral process, accentuating its economy's fundamental characteristics. Robust political and governance institutions, a commitment to open trade and investment, global integration, monetary stability, and an independent judiciary distinguish the country. Furthermore, India possesses a young, educated, and skilled workforce with remarkable adaptability and a positive outlook. Significant advancements in infrastructure, energy, and technology continue to contribute to the evolving economic landscape. Collectively, these elements play a crucial role in driving economic growth and exerting a favourable impact on stock market performance. It is noteworthy that, regardless of the political party in office, a consistent focus remains on sustaining India's growth trajectory. Political entities recognise that fostering economic development contributes to national progress and enhances their prospects for electoral success. Consequently, the interplay between governance and economic performance remains vital in India's financial landscape narrative.

5.2 Discussion of Research Question Two

Statistical and descriptive analyses of hypothesis H3 provide significant insights into the second research question: Do investors exhibit financial biases in their decision-making processes that lead to market mispricing?

The statistical t-test results for H3, based on survey research methodology, revealed statistically significant biases exhibited by investors. This aspect of the study highlights how collective BF principles manifest during Indian general electoral periods. These analyses highlight the factors that contribute to irrational market reactions and emphasise the cognitive and emotional biases that investors tend to exhibit. Understanding these biases is crucial, as they can skew an investor's perception and lead to suboptimal decision-making.

The primary aim of this research was to statistically substantiate the prevalence of biases among investors. By establishing biases in investors that favour the hypothesis H3, the study aimed to explain the cause-and-effect relationships between these biases and the abnormal behaviours frequently observed in stock market dynamics. Such an explanation reiterates basic principles, models, and theories of behavioural finance.

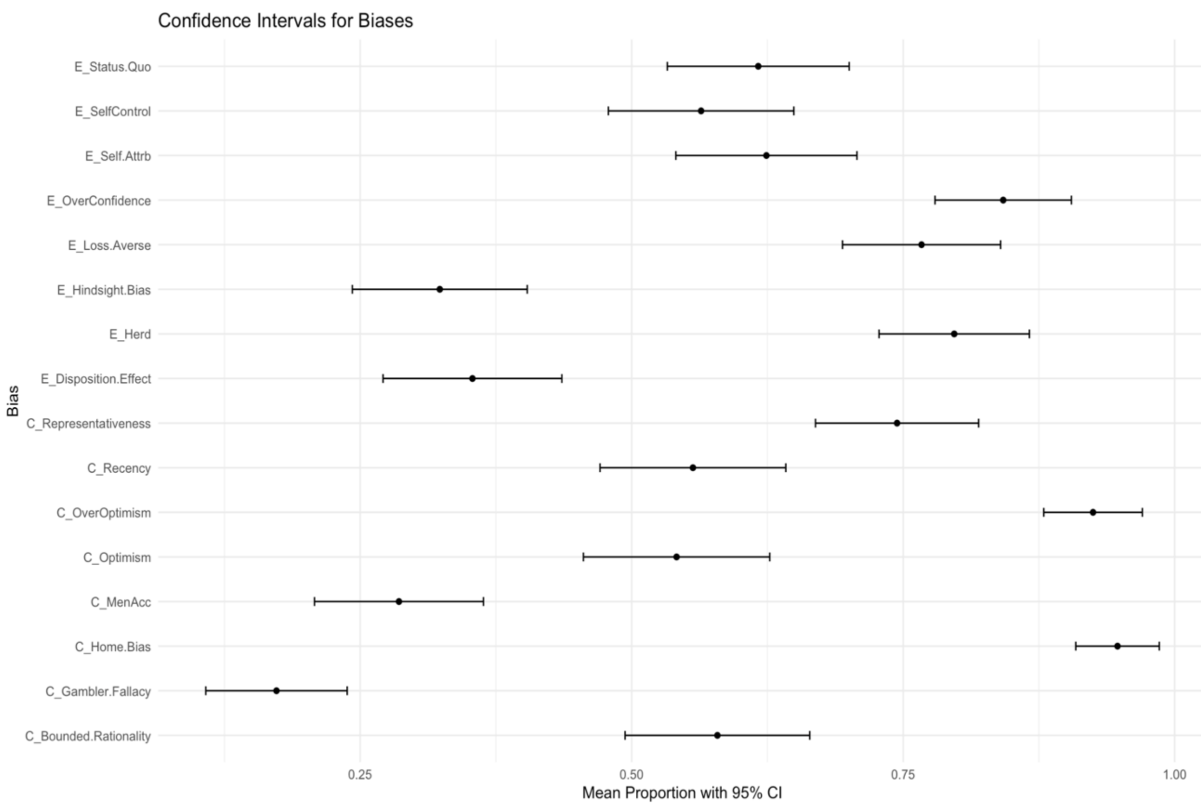
Although not mandated by the research requirement, the researcher incorporated a series of additional tests and analytical methods to identify meaningful associations and correlations between biases and various demographic profiles of investors. These profiles included factors such as age, gender, income, education level, and trading experience. By analysing these demographics, the research aimed to uncover patterns that might indicate how specific groups of investors are more prone to certain biases, thereby enriching our understanding of BF.

The study delved into the relationships between specific independent biases and investors' demographic characteristics. This nuanced approach enabled a more sophisticated understanding of how various personal attributes may influence investment behaviour and decision-making processes. To accomplish this, the researchers employed a variety of descriptive and statistical tests using platforms such as R and MS Excel, which facilitated a thorough analysis of the data.

Confidence Intervals of Independent Biases at 95% Confidence Level:

The confidence interval is the range of values derived from a sample that is likely to contain the true value of the population parameter, with a 95% confidence level.

Figure 17: Confidence Intervals (CI) of Independent Biases



Source: Created by the author

As illustrated in Figure 18, all sixteen independent biases in the study indicate that the population of investors will possess all biases well above zero value (unbiased investors), albeit across a diverse range. These findings highlighted the varying degrees of influence specific biases may exert over investors, drawing attention to how some biases can significantly impact decision-making more than others. Overall, the research provided valuable insights into the complex interplay between psychological biases and market behaviour, reinforcing the essential role of BF in understanding and interpreting financial markets. This understanding can ultimately help develop strategies to mitigate the detrimental effects of such biases on investment decisions and market efficiency.

Traditional economists have frequently argued that errors arising from behavioural biases are independent among individuals, allowing them to offset each other and ultimately resulting in a ‘net-zero effect’ on market pricing. However, this viewpoint of traditional economists is fundamentally flawed in its assumption that the financial impacts of behavioural biases, both positive and negative, are independent too. Moreover, as noted in the book “Behavioural Finance” (Chandra, 2020), Tversky and Kahneman challenge their view, asserting that successful individuals share similar heuristics that have proven effective throughout our evolutionary history. As a result, the human race is likely to experience biases in comparable ways.

To reject the “net-zero effect” theory, the current research employed a single-factor ANOVA test to determine whether the overall mean bias value across all biases varied significantly between respondents (Table 14). Additionally, it aimed to determine whether the mean values of the various independent biases among investors differed significantly between biases (Table 13).

Table 12: ANOVA Test Results on Investors' Independent Biases

ANOVA- 1Factor -Alpha 0.05						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Biases	110.7406	15	7.382704	38.43795	7E-100	1.670915
Within Biases	424.0863	2208	0.192068			
Total	534.8269	2223				
Result	The means are SIGNIFICANTly different between Biases					

Source: Created by the author

As per Table 13, the p-value is less than the significance level of 0.05, and the F-value is more than the F-critical value, which signifies that the mean strength of each of the sixteen independent biases varies significantly between them.

Table 13: ANOVA test Results on Investor Respondents

ANOVA- 1 Factor	ALFA = 0.05					
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Respondants	36.26439	138	0.262785	1.098975	0.210212	1.214612
Within Respondant	498.5625	2085	0.239119			
Total	534.8269	2223				
Result	The means are NOT SIGNIFICANTly different between Responder					

Source: Created by the Author

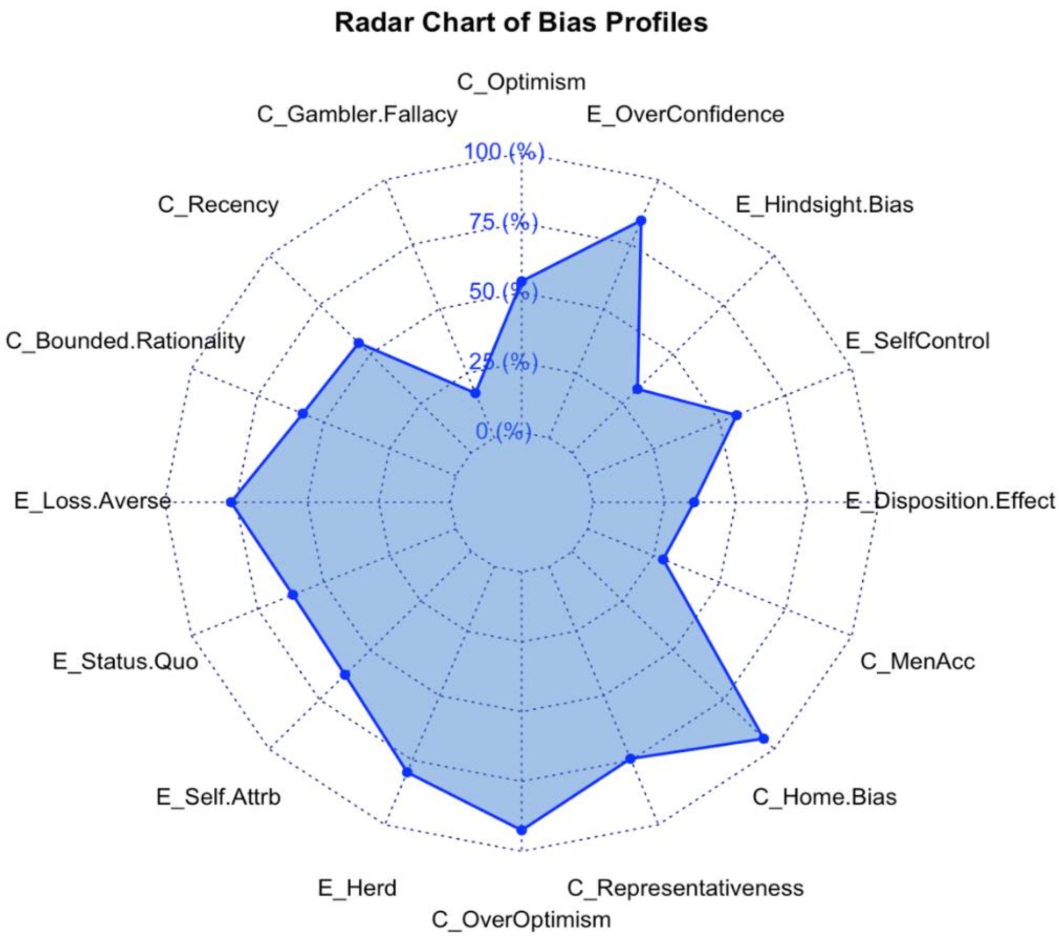
According to Table 14, the p-value exceeds the significance level of 0.05, and the F-value is less than the F-critical value, indicating that the mean strength of overall bias in respondents does not vary significantly between them.

Results derived from ANOVA single-factor statistical tests indicated that while a significant difference exists in the independent biases exhibited by investors, there is a considerable level of overall bias in investors, which does not vary significantly between them.

Moreover, the descriptive results of the Variance-Covariance test (see Appendix F) reveal that although the portfolio variance (which accounts for covariances between biases) decreased to 1.7% from the simple weighted average variance of 19% across all biases, it failed to reach the target value of 0% as suggested by BF critiques. Consequently, the findings from both the ANOVA and Variance-Covariance portfolio analysis indicate that the argument for a net-zero effect is not substantiated.

While the scope of the research did not entail a thorough analysis of specific independent biases of investors and their relationships with their demographic profiles, it is worth noting that the results from the descriptive tests, as dipicted in the radar chart in Fig 18 and box plots in Fig 19, indicate some interesting observations, which could inspire interest and open avenues for future research.

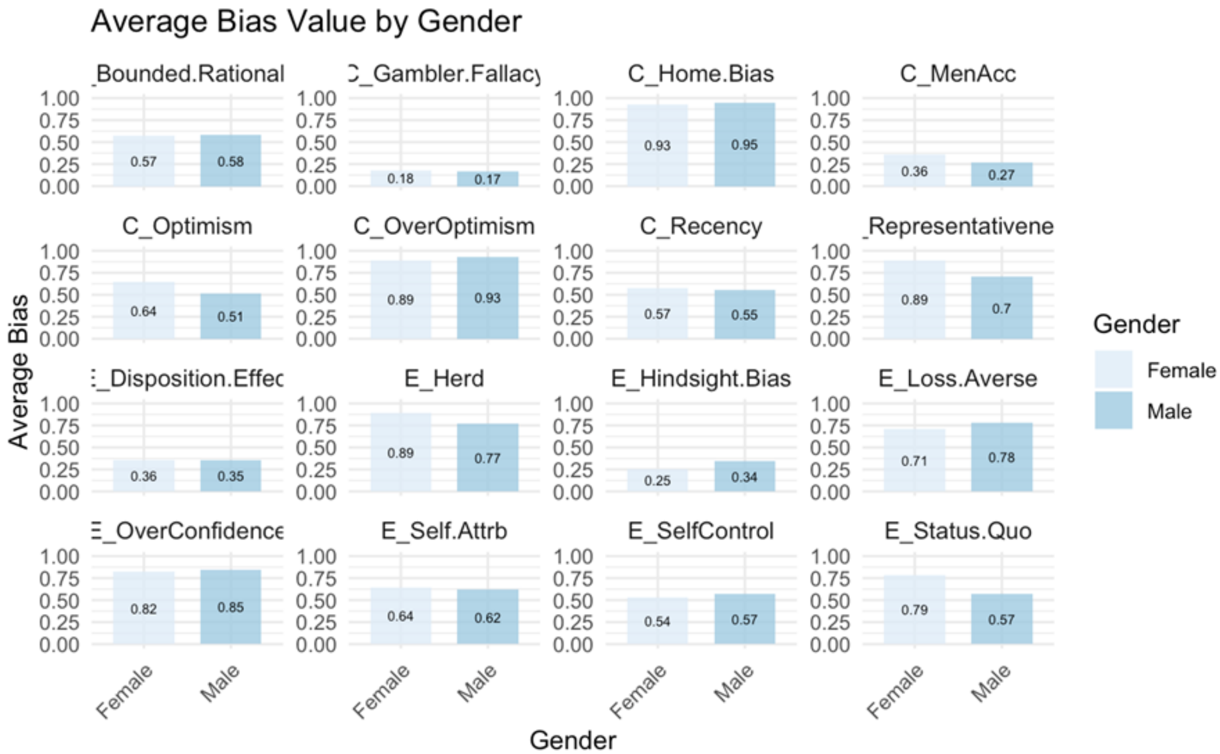
Figure 18: Radar Charts of Biases

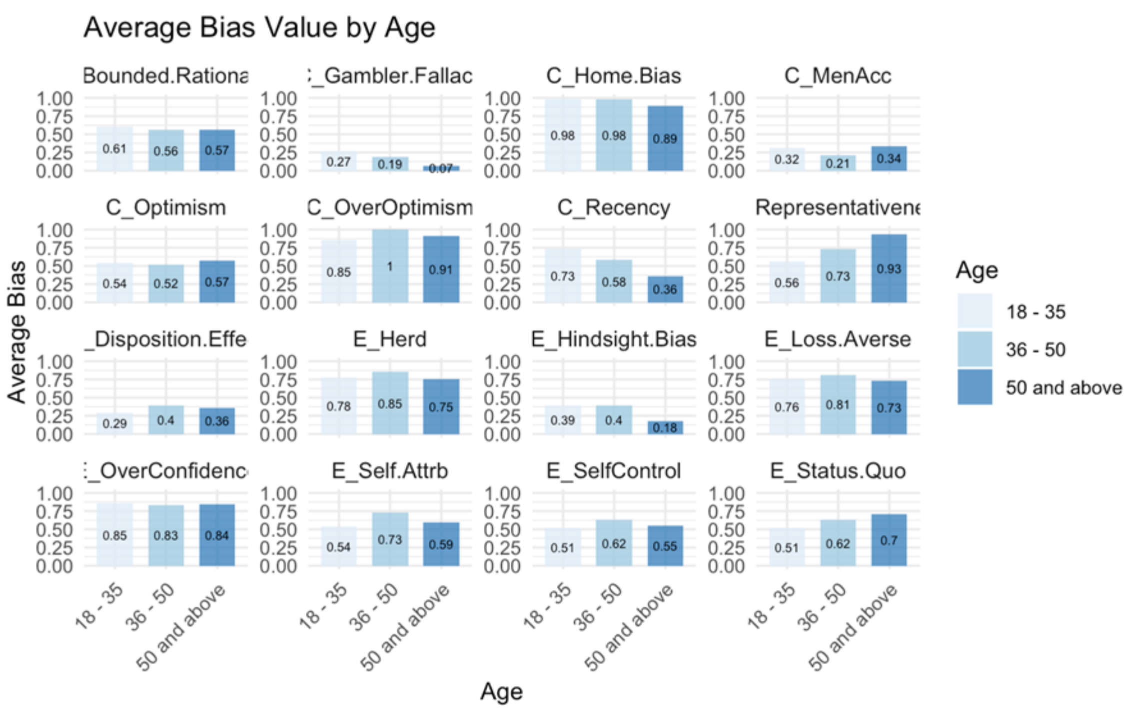


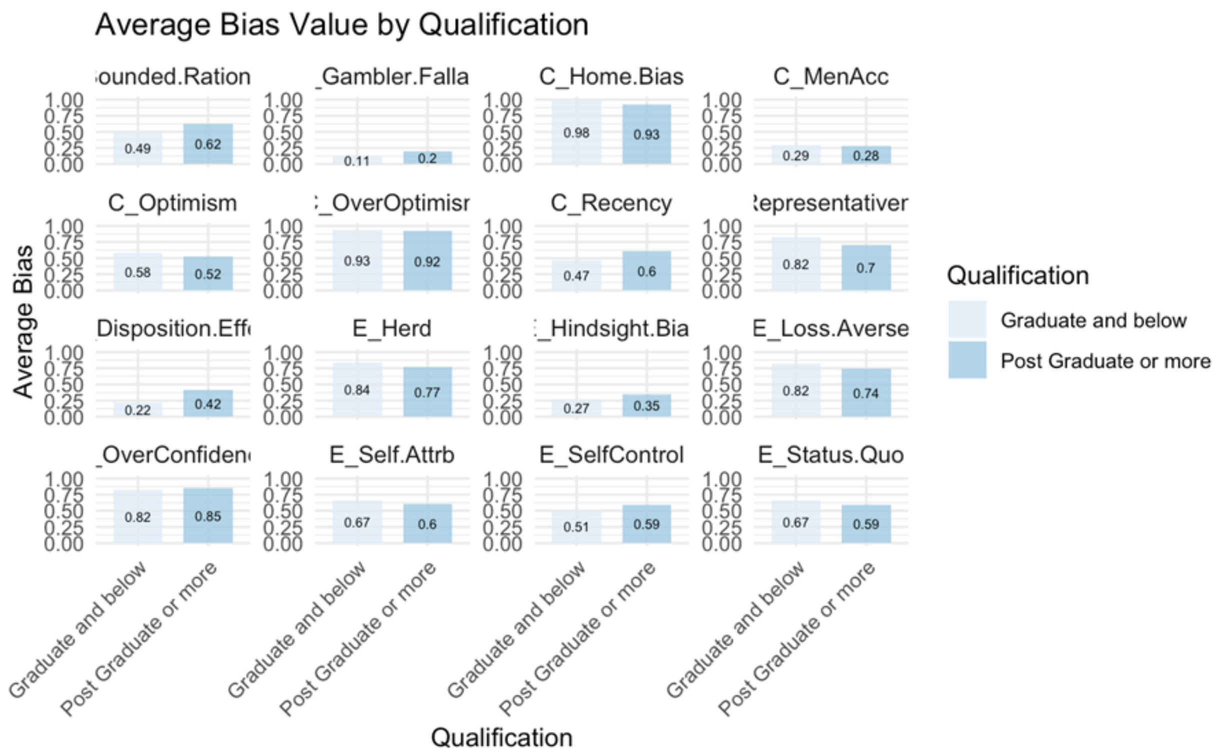
Source: Created by the author

A Radar Chart or Spider Chart provides a useful visual tool for comparing investors' specific biases at a glance. As seen in the chart, “Over-optimism,” “Home Bias,” and “Representativeness” scored high among cognitive biases, while “Overconfidence,” “Loss Aversion,” and “Herding” biases scored high in the emotional biases.

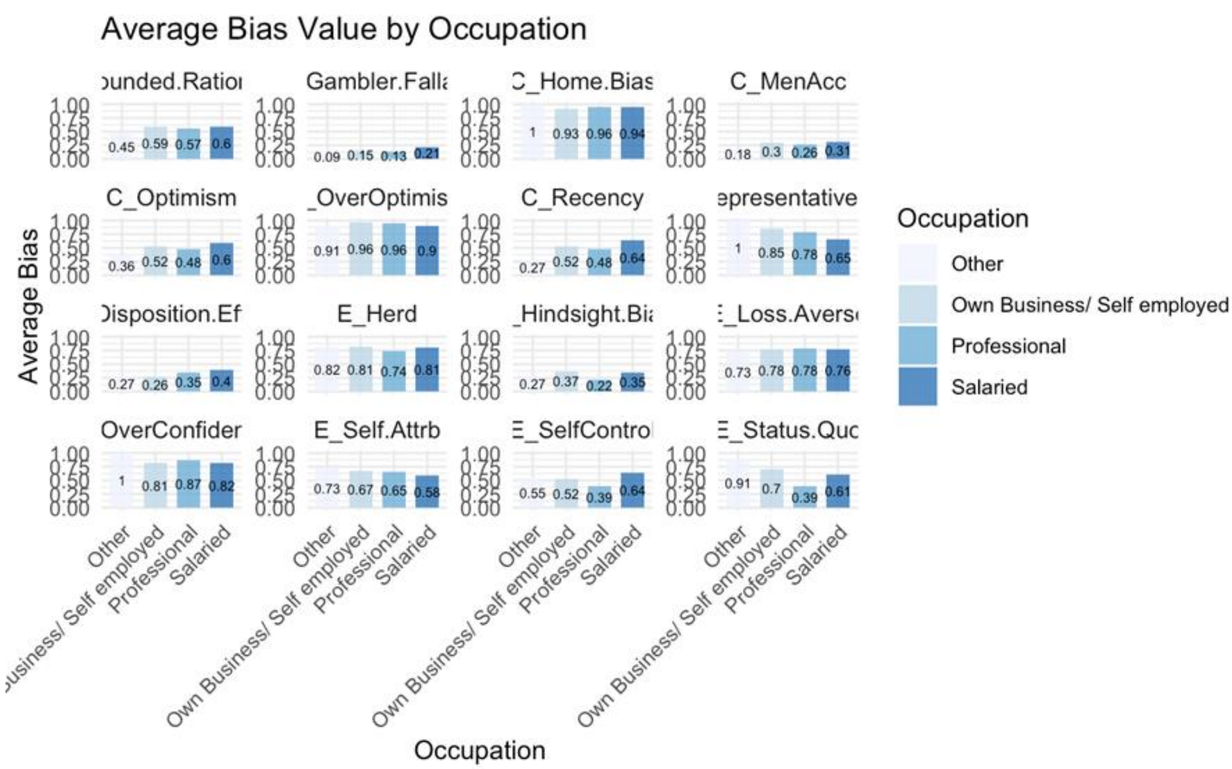
Figure 19: Average Bias by Various Demographic Profiles of Investors



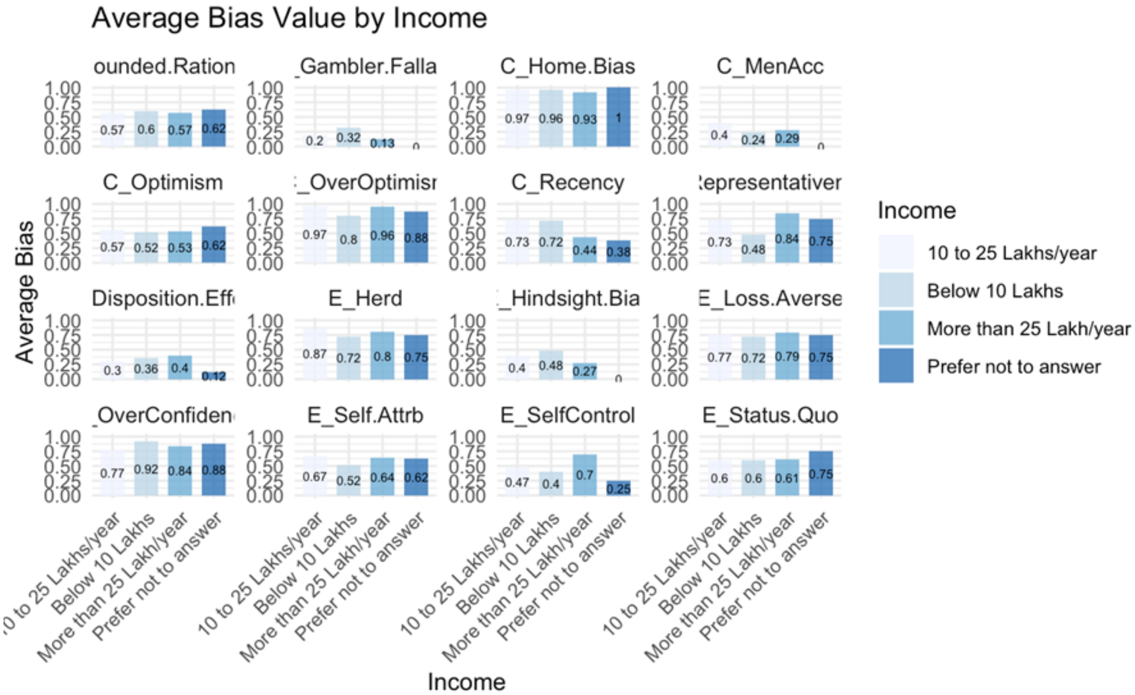


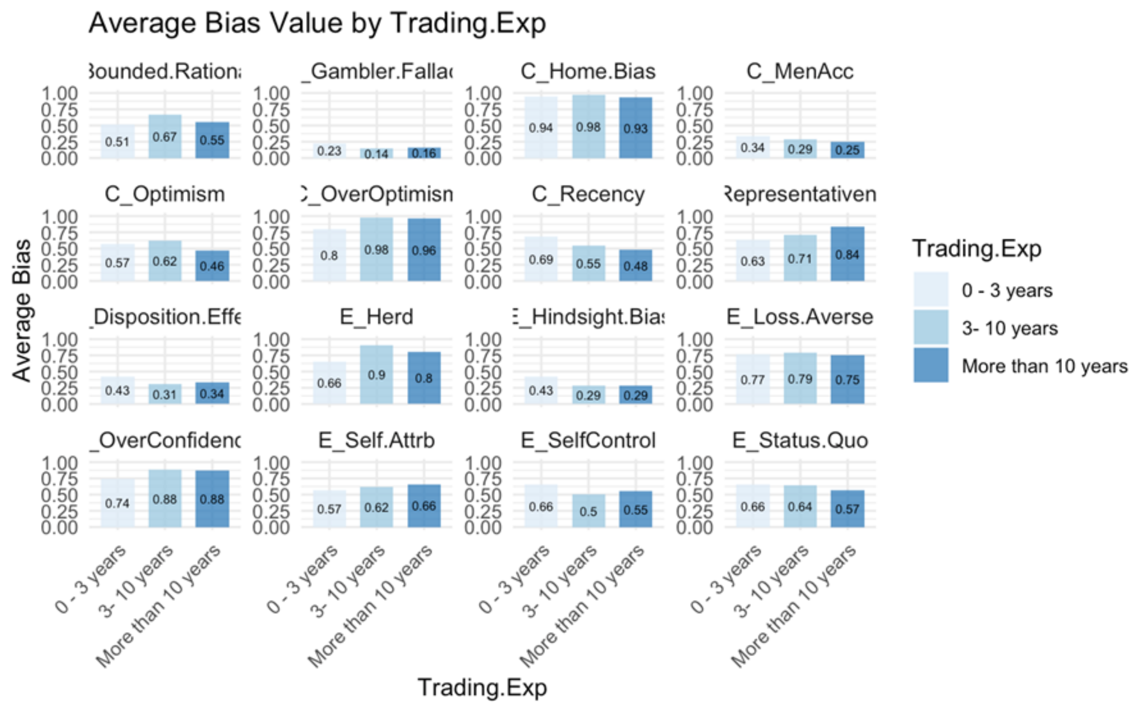


Average Bias Value by Qualification
Average Bias
Qualification
Graduate and below
Post Graduate or more
C_Home.Bias
C_MenAcc
C_Optimism
C_Recency
E_Herd
E_Loss.Averse
E_Self.Attrb
E_SelfControl
E_Status.Quo



Average Bias Value by Occupation
Average Bias
Occupation
Other
Own Business/ Self employed
Professional
Salaried
C_MenAcc
C_Optimism
C_Recency
E_Herd
E_Self.Attrb





Source: Created by the author

Overall, the study not only reinforces the impact of general elections on stock market conditions but also enriches the discourse on investor psychology and its financial implications within the context of situational uncertainties.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

The Indian GE events are a notable example of high political uncertainty, which can invoke financial biases in investors and result in stock market abnormalities.

The impact of a country's economic policies, particularly fiscal policies, on its stock markets is well established in the literature review. Focusing on India, it highlights how political events, such as the Indian general elections, introduce uncertainty, influencing stock market behaviour as investors anticipate changes in government economic policies through their biased logic and emotions. Financial analysts try to incorporate all relevant information, but their behavioural biases often lead to inconsistent predictions and market valuations.

The study examines the emotional and cognitive biases that influence investors' financial decisions. Emotional biases emanate from people's reactive nature, while cognitive biases involve shortcuts the brain uses in decision-making that are more reflective. Both systems can lead to errors in decision-making, particularly in uncertain situations. The research builds on the idea that classical financial models, which assume rational investor behaviour, are flawed, especially when political events, such as the Indian General Elections, lead to heightened economic future uncertainty.

Focusing on behavioural finance, the study explains how psychological factors impact investment decisions during election periods. It analysed data from five GEs in India between 2000 and 2024 to understand the Indian stock market's returns and volatility, as well as the influence of investors' biases. The findings aim to contribute to the field of BF, offering insights into the academic and practical implications of behavioural biases in investment strategies.

The empirical evidence undermining the classical assumption that investors consistently engage in rational decision-making is well-documented within the literature review. With contradictory empirical evidence, classical finance is approaching its limit of usefulness (Chandra, 2020); the author of the book “Behavioural Finance” quotes Michael J. Mauboussin, “People are adaptive and not fully informed and deal with one another. Ideally, we should seek to explain the empirical findings with an approach that aligns with how people behave.” He suggests that the capital market may be considered a “complex adaptive system” (CAS). “Complex” means that there is much interaction; “Adaptive” means that the agents change and evolve, and the “System” becomes more complicated than the sum of its parts. CAS appears to align more closely with reality than classical financial theories. When specific decision rules become pervasive, homogeneity of views may lead to booms and crashes. Aggregate behaviour is very complex because of interaction effects.

The study examined two critical research questions:

1. Do the Indian stock markets diverge from their intrinsic pricing, as outlined by classical financial theories, during periods of political uncertainty, such as during GEs in India?
2. Do investors exhibit financial biases in their decision-making processes, leading to mispricing in the stock market?

The central hypotheis of the research (H), through its sub hypotheses H1, H2 and H3 together answered the two research questions by employing appropriate statistical testing methods.

The sub hypotheses (H1) and (H2) confidently addressed the first research question, establishing that Indian stock markets significantly deviate from their intrinsic values during Indian GEs, resulting in markedly higher market returns in the medium term and increased volatility in the short term.

Sub -hypothesis (H3) directly addressed the second question, asserting that investors exhibit substantial biases in their financial decision-making, resulting in predictable market anomalies during the Indian GEs.

Together, they decisively rejected the null hypothesis (H0), which posits that in politically turbulent times, such as the Indian General Elections (GEs), stock markets operate efficiently, driven by rational investors who flawlessly and instantaneously integrate all available information into stock prices. Such investors are presumed to be unaffected by emotional or cognitive biases that can lead to market mispricing and predictability.

The testing methods for Hypotheses 1 and 2 were exclusively based on secondary quantitative data, while Hypothesis 3 incorporated survey methodology to collect primary data. which contained both descriptive and statistical test approaches.

“R and R Studio” were used for large-scale data analysis to test hypotheses H1 and H2, while Microsoft Excel tools were employed to process the statistical t-tests on the H3 survey data.

To explore the survey data further, a series of descriptive and statistical analyses, including visualisation tools, chi-squared tests, Cramer’s V tests, and linear regressions, were employed to observe patterns and analyse associations, relationships and correlations between investors' demographic profiles and their financial biases. The versatility of “R” tools was utilised for demographic analysis and data visualisation.

Political uncertainty generally peaks just before the announcement of election results, a trend that can be generalised through the short-term volatility tests using the IndiaVIX fear gauge index. However, markets often experience a recovery once concerns surrounding the new government and its economic policies begin to ease, as evidenced by medium-term market returns using NSE’s NIFTRI index.

Despite the inherent volatility during election cycles, India's stock markets have demonstrated remarkable resilience, with a compounded annual growth rate of 14.92% from 2000 to 2024, as indicated by NSE data. This growth reflects the market's robustness in the face of various political changes, underscoring investors' adaptability in response to shifting government landscapes.

Several key factors contribute to this sustained economic growth. First and foremost, India's strong political and economic institutions provide a foundation of stability that instils confidence in both domestic and international investors. Additionally, the country's commitment to trade enables it to engage effectively with the global economy, further fuelling growth prospects.

Monetary stability is another crucial element, as it allows for predictable fiscal policies that support business investment. Moreover, India boasts a skilled workforce that continuously adapts to new technologies and global market demands, providing a competitive edge in many industries.

Infrastructure advancements also play a significant role, as improvements in transportation, energy, and digital connectivity enhance productivity and facilitate business operations.

Regardless of which political party assumes power, the overarching focus of governance tends to remain on stimulating economic development. This consistent commitment to growth reinforces the long-term stability of India's financial markets, allowing them to weather political transitions and maintain investor confidence. As a result, even amidst changes in political leadership, the outlook for India’s economic landscape remains positive and resilient.

6.2 Implications

Periods of uncertainties during Indian GEs can present valuable opportunities for medium-term investors to acquire quality assets at lower prices due to predictable market behaviour. Conversely, short-term traders must employ strong risk management strategies while minimising downside risks. Investors should periodically assess their biases and risk tolerance levels to formulate a clear investment plan.

The implications of behavioural financial theories highlight that stock market valuations, although assessed through traditional models, fluctuate beyond their range due to uncertainties. Markets are collectively more intelligent than individual investors, prompting experts to incorporate market behaviour over classical models in pricing the markets. Furthermore, while markets operate effectively during normal times, they become predictably abnormal during periods of high uncertainty, as participants tend to react in a similar manner, often driven by their biases.

Research indicates that investors' psychological biases have a significant impact on financial decision-making, particularly during uncertain times. BF, a branch of experimental economics, involves practitioners, financial planners, and advisors who seek to understand the psychological biases that affect investors. By addressing these biases, investors can aim to resolve the persistent issues they encounter in the stock markets and reduce the anomalies observed in the market. Self-awareness of biases, adaptive investment strategies, goal-based portfolio diversification, emotional control, professional advice from behavioural finance experts, mindful use of technologically driven trading platforms, and practical and balanced regulatory policies can improve profitability at reduced risks to investors.

BF models serve as an essential complement to traditional finance models. BPT and BAPM are grounded in the principles of MPT and CAPM. The BF theories adopt a prescriptive approach by integrating concepts of crowd psychology and group behaviour into investment management. Financial advisors and practitioners can gain insights into the standard cognitive and emotional biases and errors frequently exhibited by their clients. They can recommend strategies by understanding these behavioural tendencies, fostering greater self-control and improved decision-making, along with established finance and economic theories. Pure rationality without emotions can be just as detrimental as emotions without reason. According to neuro-finance, the best investment results are possible with the right balance of emotion and reason. People are "normal," with a full range of wants: utilitarian, social, and emotional, driven by both cognitive and emotional constituents. Factoring in these elements of the market behaviour should be the way forward in the financial modelling techniques.

The key takeaway from the research findings is that they provide a basis for developing a hybrid thought process for trading strategies and investment philosophies by leveraging concepts from behavioural finance theories and models alongside classical ones.

6.3 Recommendations for Future Research

At the broader level, two recommendations for future studies based on the current research and its limitations can be suggested:

- Longitudinal Studies on Bias Evolution: Conduct longitudinal studies to assess how behavioural biases evolve, particularly during uncertain market conditions. This can help identify patterns and triggers that influence investor behaviour, providing insights into the persistence or change of biases over time.

- Impact of Technology on Investors' Investment Decisions: Investigate the influence of technology on investor behaviour. As technology-assisted programs drive an increasing number of online trading and investing platforms, the growth in investors' trading activities is becoming increasingly evident. Studies could focus on how automation and advanced AI features, now available to investors, affect their investment biases, particularly during significant market events or crises.

6.4 Conclusion

The research demonstrates that investor behavioural biases play a crucial role in shaping stock market dynamics, especially during uncertain times such as General Elections. The heightened anxiety associated with electoral events intensifies cognitive and emotional biases among investors, leading to irrational investment decisions that disrupt market behaviour.

BF unequivocally complements traditional finance theories, primarily through frameworks like "BPT". This theory adopts a prescriptive approach that seamlessly integrates concepts of crowd psychology and group behaviour into effective portfolio management practices. Financial professionals stand to gain valuable insights by recognising the cognitive and emotional biases frequently exhibited by their clients. By understanding these behavioural tendencies, finance practitioners can refine their strategies, enhance self-control, and improve decision-making, ultimately strengthening economic and financial theories.

It is essential to acknowledge that the belief in pure rationality, without emotional consideration, can be as harmful as a complete lack of reason during emotionally charged situations. Neurofinance asserts that optimal investment outcomes can be achieved by striking the right balance between emotion and reason. Individuals are inherently complex, driven by a spectrum of desires—utilitarian, social, and emotional—each influenced by cognitive and emotional factors. By incorporating these dimensions into the analysis of market behaviour, we pave the way for a more sophisticated approach to financial modelling.

Tailored recommendations can be made at two key levels – investors and regulators- to enhance overall capital market discipline and performance, ultimately benefiting financial markets. Acknowledging and accommodating these biases, investors are encouraged to consider the following strategies:

- Goal-based Portfolios: Investors should prioritise goal-based diversification of portfolios to a single portfolio built purely on its utilitarian efficiency. Well-diversified portfolios, designed to accomplish all utilitarian, social, and emotional goals, diminish the potential impact of any singular event.
- Systematic Investing: Adopting a systematic investment approach, such as rupee-cost averaging, can help investors maintain discipline in their buying strategy, unaffected by prevailing market sentiment. This strategy helps reduce the tendency to react emotionally.
- Long-Term Focus: Maintaining a long-term investment perspective can help investors resist the tendency to make impulsive decisions influenced by short-term events. Historical trends often indicate a market recovery over time, mitigating the effects of transient uncertainties.

- Behavioural Awareness: Engaging in self-reflection or consulting with financial advisors knowledgeable in BF can greatly aid investors in recognising their inherent biases, thereby fostering more informed decision-making, particularly during volatile periods.

- Technological Assistance: Mindfully adopting technology-driven investment platforms for improved investment management.

Policymakers and market regulators play a crucial role in establishing an environment that mitigates the impact of behavioural biases on investor decision-making. These entities can foster conditions that promote improved investment behaviours by implementing effective strategies and frameworks. The following measures are recommended:

- Enhancing Market Transparency: Regulatory bodies should promote clear communication by mandating that companies provide accurate and timely disclosures regarding their financial conditions and the prevailing market landscape. They should also enforce regulations against unscientific and biased opinions and exit polls during elections. Such transparency enables investors to make decisions grounded in empirical evidence rather than emotional impulses. Standardising reporting formats and providing timely updates can significantly diminish uncertainty and prevent overreactions during volatile market periods.

- Investor Education Programs on BF: Policymakers should allocate resources to educational initiatives to increase investors' awareness of BF principles. These campaigns are crucial for equipping individuals with the knowledge to effectively navigate their cognitive biases.

- Encouraging Long-Term Investing: Introducing tax incentives for long-term investments can disincentivise short-term trading driven by emotional reactions. For instance, tax benefits for assets held for over a year can motivate investors to adopt a long-term perspective, thereby mitigating the volatility associated with impulsive decision-making.

- Promoting Diverse Investment Products: Regulators can facilitate the development of diverse financial instruments that cater to multiple risk profiles, enabling investors to select plans tailored to their specific investment goals. This diversification allows for investors to construct balanced portfolios that cater to their utilitarian, expressive, and emotional needs.
- Implementing BF Principles: Integrating BF principles into regulatory policies can help create systems that nudge investors toward more favourable decision-making outcomes. For example, the establishment of "default options" in retirement accounts can be designed to promote automatic savings and investments, thereby mitigating the effects of procrastination and indecision.
- Monitoring Market Sentiment: Regulators may consider investing in tools and indicators to actively monitor market sentiment and behavioural trends. By assessing investor behaviour and market psychology, regulators can intervene in irrational exuberance or panic, potentially stabilising markets during periods of turbulence.
- Strengthening Enforcement of Ethical Standards: Strictly enforcing regulations against misleading advertisements, fraudulent schemes, and insider trading is essential in cultivating investor confidence. When investors possess a strong level of trust in the markets, they are less inclined to make impulsive decisions driven by fear or speculation.

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APPENDIX A

SURVEY COVER NOTE AND INFORMED CONSENT

1.1 Cover note of the survey form:

Hello, thank you for agreeing to fill out this survey! This may take only 10-15 minutes of your time.

This survey is being conducted as part of Arun Singhania's DBA (Doctorate in Business Administration) academic program from SSBM, Geneva, Switzerland.

- **Section One** of this survey may require **10 to 12 minutes** of your precious time to answer **16 simple questions** about your opinion and reactions under various situations.
- **Questions 17 to 24** require **demographic** information like your name, age, etc.. (these are important for segment-wise analysis of the data collected through the survey form).

Please note that this questionnaire is not an evaluation of your performance as there are no right or wrong answers to these questions!

Each question is about human nature and behaviour, the answer to which may vary from person to person. So, just be yourself. Your honest and unbiased answers will help the researcher make a reliable conclusion. Your data will kept confidential and it will be used only for academic analysis and not for any other commercial purposes.

Your answers contribute to a highly specialised analysis of BF and stock markets in India. Upon completing the survey in full, you may give your email id in the last question of this survey form, if you wish to get the summary of the final report later.

APPENDIX B

CODES FOR HYPOTHESIS H1

B.1 Code for Data Cleaning and Data Wrangling in “R”

````
#1. Data Cleaning and Data Wrangling

#Load the data into R workspace

```{r}

#setwd("~/Desktop")

setwd("~/Desktop/R files - Research")

library(readr)

library(dplyr)

library(lubridate)

niftyTR <- read.csv("niftyTR.csv")

summary(niftyTR)

niftyTR <- niftyTR |>

```

#After viewing the summary, it appears that the 'Date' column is of data

class 'Character'. To properly analyse the data, we load 'lubridate'
````

package to change the class of "Date" column to the appropriate date

format (dd-mm-yy).

```{r}
library(lubridate)

niftyTR$Price <- as.numeric(niftyTR$Price)

class(niftyTR$Price)
```

#Selecting only the necessary columns for analysis - "Date" and "Price"

```{r}
niftyTR <- niftyTR |>

  select("Date", "Price")

summary(niftyTR)
```

#Ensuring that the Date column is correctly classed and read in R

```{r}
niftyTR$Date <- dmy(niftyTR$Date)

class(niftyTR$Date)
```

#Ensuring that the dataset is in chronological i.e. ascending order of

Date

```{r}

niftyTR <- niftyTR[order(niftyTR$Date), ]

```

B.2 Code for Making the appropriate subsets in “R”

```
#Medium- Term Analysis:

# Function to calculate avg_yrly_rtn

calculate_avg_yrly_rtn <- function(data, start_date_range, end_date_range,

base_start_date, base_end_date) {

  numerator_mean <- mean(data$Price[data$Date >= start_date_range &

data$Date <= end_date_range])

  denominator_mean <- mean(data$Price[data$Date >= base_start_date &

data$Date <= base_end_date])

  avg_yrly_rtn <- numerator_mean / denominator_mean
```

```
  return(avg_yrly_rtn)

}

# Calculate avg_yrly_rtn for each election year

avg_yrly_rtn_2004 <- calculate_avg_yrly_rtn(niftyTR, "2004-11-01",

"2004-12-01", "2003-11-01", "2003-12-01")

avg_yrly_rtn_2009 <- calculate_avg_yrly_rtn(niftyTR, "2009-11-01",

"2009-12-01", "2008-11-01", "2008-12-01")

avg_yrly_rtn_2014 <- calculate_avg_yrly_rtn(niftyTR, "2014-11-01",

"2014-12-01", "2013-11-01", "2013-12-01")

avg_yrly_rtn_2019 <- calculate_avg_yrly_rtn(niftyTR, "2019-11-01",

"2019-12-01", "2018-11-01", "2018-12-01")

avg_yrly_rtn_2024 <- calculate_avg_yrly_rtn(niftyTR, "2024-11-01",

"2024-12-01", "2023-11-01", "2023-12-01")

# Create subsets mt_1999, mt_2004, mt_2009, mt_2014, and mt_2019

#mt_1999 <- data.frame(avg_yrly_rtn = avg_yrly_rtn_1999)

mt_2004 <- data.frame(avg_yrly_rtn = avg_yrly_rtn_2004)

mt_2009 <- data.frame(avg_yrly_rtn = avg_yrly_rtn_2009)

mt_2014 <- data.frame(avg_yrly_rtn = avg_yrly_rtn_2014)
```

~~~
mt_2019 <- data.frame(avg_yrly_rtn = avg_yrly_rtn_2019)

mt_2024 <- data.frame(avg_yrly_rtn = avg_yrly_rtn_2024)

# Print the subsets

print("mt_2004:")

print(mt_2004)

print("mt_2009:")

print(mt_2009)

print("mt_2014:")

print(mt_2014)

print("mt_2019:")

print(mt_2019)

print("mt_2024:")

print(mt_2024)

```

```{r}

# Combine Avg yearly return values into a vector

election_mediumterm <- c(mt_2004$avg_yrly_rtn[1], mt_2009$avg_yrly_rtn[1],

mt_2014$avg_yrly_rtn[1], mt_2019$avg_yrly_rtn[1], mt_2024$avg_yrly_rtn[1])
~~~

election_mediumterm

```
```

#Making other medium term rolling subsets

```
```{r}

# Define the rolling window size

rolling_window_size <- 252  #Chosen number based on avg number of business

days in a calendar year

# Create an empty vector to store returns values

returns_vector <- numeric()

# Function to calculate returns

calculate_returns <- function(subset) {

  start_value <- subset$Price[1]

  end_value <- subset$Price[length(subset$Price)]

    # Counting unique years

  returns <- ((end_value / start_value))

  return(returns)

}

# Iterate through the date ranges and calculate returns for each subset
```
```

```
for (i in 1:(length(niftyTR$Date) - rolling_window_size + 1)) {

  subset <- niftyTR[i:(i + rolling_window_size - 1), ]

  returns <- calculate_returns(subset)

  returns_vector[i] <- returns

}

# Define the ranges of dates to be removed

date_ranges <- list(

  c(as.Date("2003-11-01"), as.Date("2004-12-01")),

  c(as.Date("2008-11-01"), as.Date("2009-12-01")),

  c(as.Date("2013-11-01"), as.Date("2014-12-01")),

  c(as.Date("2018-11-01"), as.Date("2019-12-01")),

  c(as.Date("2023-11-01"), as.Date("2024-12-01"))

)

# Identify indices corresponding to the date ranges to be removed

indices_to_remove <- which(sapply(niftyTR$Date, function(date) {

  any(sapply(date_ranges, function(range) {

    date >= range[1] & date <= range[2]

})) }))
```

Remove returns corresponding to the specified dates

returns_vector <- returns_vector[-indices_to_remove]

Print the length of the returns vector

print(length(returns_vector))

``

B.3 Code for Hypothesis Testing using t-test in "R"

#t-test:

Assuming you have the 'returns_vector' and 'election_mediumterm' lists

available

Perform t-test between the combined returns and the election medium-term

returns

ttest_result <- t.test(election_mediumterm, returns_vector, alternative =

"greater", var.equal = TRUE, conf.level = 0.95)

Print the t-test result

print(ttest_result)

```

<Appendix no.> Result of t-test for medium term analysis
```

```
Two Sample t-test

data:  election_mediumterm and returns_vector
t = 1.765, df = 4992, p-value = 0.03881
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.01367493        Inf
sample estimates:
mean of x mean of y
 1.350580  1.149167
```

B.4 Additional Support for using Two Sample t-test

#Additional support for using Student's Two Sample t-test which assumes

same variance of both samples

Variances of the 2 vectors

```{r}

var(election_mediumterm)
```

var(returns_vector)

var.test(election_mediumterm, returns_vector)

```

```
[1] 0.06552465

[1] 0.06504622

	F test to compare two variances

data: election_mediumterm and returns_vector
F = 1.0074, num df = 4, denom df = 4988, p-value = 0.8043
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 0.3612695 8.3193196
sample estimates:
ratio of variances
          1.007355
```
```

APPENDIX C

CODES FOR HYPOTHESIS H2

C.1 Code for Data Cleaning and Wrangling in "R"

````
```{r}

#short term analysis new with VIX

# Load necessary libraries

library(dplyr)

library(readr)

library(lubridate)

# Load the Vix data and select the relevant columns to an object vix

vix <- read_csv("vix.csv")

vix <- vix |>

  select("Date","Open")

# Convert the date column to Date type

vix$Date <- dmy(vix$Date)

class(vix$Date)

#summary(vix)

```
````

```{r}

# Define the intervals to be excluded from rolling data set (21 days

before and 7 days after specific dates)

intervals <- list(

  list(start = as.Date("2009-05-16") -21 , end = as.Date("2009-05-16")+7),

  list(start = as.Date("2014-05-16") - 21, end = as.Date("2014-05-18") +

7),

  list(start = as.Date("2019-05-23") - 21, end = as.Date("2019-05-23")+7),

  list(start = as.Date("2024-06-04")-21, end = as.Date("2024-06-04")+7)

)

```

C.2 Code for Creating the Election Subsets and Non-Election Subsets in "R"

```{r}



# Filter data based to make election short term sub-sets with the

filtering logic of 21 days before the election result date and 7 days

after
```

````
st2009 <- vix %>% filter(Date >= "2009-04-25" & Date <= "2009-05-24")

st2014 <- vix %>% filter(Date >= "2014-04-25" & Date <= "2014-05-24")

st2019 <- vix %>% filter(Date >= "2019-05-02" & Date <= "2019-05-31")

st2024 <- vix %>% filter(Date >= "2024-05-14" & Date <= "2024-06-11")

# Print the first few rows of each subset to verify

head(st2009)

head(st2014)

head(st2019)

head(st2024)

```

```{r}

# Create a function to check if a date is within any excluded interval

is_excluded <- function(Date, intervals) {

  for (interval in intervals) {

    if (Date >= interval$start & Date <= interval$end) {

      return(TRUE)

} }

  return(FALSE)
````

```
}

```

```{r}

# Create an empty list to store the rolling subsets

rolling_subsets <- list()

# Calculate rolling subsets with window size 21

for (i in 1:(nrow(vix) - 21 + 1)) {

  subset <- vix[i:(i + 21 - 1), ]

  # Check if any date in the subset is within the excluded intervals

  if (!any(sapply(subset$Date, is_excluded, intervals))) {

    rolling_subsets[[length(rolling_subsets) + 1]] <- subset

  }

}

# Check the number of valid rolling subsets

length(rolling_subsets)

```
```

## C.3 Code for Hypothesis Testing using t-test in "R"
```

```
```{r}

# Define the special subsets in a list

election_subsets <- list(st2009, st2014, st2019, st2024)

# Initialize a counter for total number of t-tests

total_tests <- 0

# Function to perform t-test between excluded subset and each rolling

subset

perform_t_tests <- function(election_subsets, rolling_subsets) {

  p_values <- sapply(rolling_subsets, function(rolling_subset) {

    t_test_result <- t.test(election_subsets$Open, rolling_subset$Open,

                            alternative = "greater", na.rm = TRUE,

var.equal=FALSE)

    return(t_test_result$p.value)

  })

  # Update the global counter for the total number of tests run

  assign("total_tests", total_tests + length(p_values), envir =

.GlobalEnv)
```
```

```
  return(p_values)

}

# Calculate the proportion of significant p-values for each election

subset

significant_proportions <- sapply(election_subsets,

function(election_subsets) {

  p_values <- perform_t_tests(election_subsets, rolling_subsets)

  proportion_significant <- mean(p_values < 0.05)

  return(proportion_significant)

})

# Print the proportions of significant p-values

print(significant_proportions)

# Print the total number of t-tests run

print(paste("Total number of t-tests performed:", total_tests))
```

C.4 Results of t-tests

```
[1] 0.9808489 0.8659420 0.7264493 0.6387164

[1] "Total number of t-tests performed: 15456"
```

APPENDIX D

CODES FOR HYPOTHESIS H3

D.1 Normality Check for Survey Data on investors' "Overall Bias" in "R"

survey_clean$Overall_Bias_Jittered <- survey_clean$Overall_Bias + runif(nrow(survey_clean), -0.01, 0.01)

ks.test(s= meanurvey_clean$Overall_Bias_Jittered, "pnorm",

mean (survey_clean$Overall_Bias_Jittered),

sd = sd(survey_clean$Overall_Bias_Jittered))

Asymptotic one-sample Kolmogorov-Smirnov test

data: survey_clean$Overall_Bias_Jittered

D = 0.10961, p-value = 0.08185

alternative hypothesis: two-sided

D.2 Steps for Statistical t-test in "MS Excel"

The five-step procedure for testing the hypothesis H3 using One sample t-test in MS Excel:

Step 1 - State the Alternate hypothesis and the Null hypothesis:

Step 2 - Select the level of significance (alpha):

Alpha is the probability of rejecting the null hypothesis when it is true.

• α= 0.01 (1%) - consumer research projects

• α= 0.05 (5%) -quality assurance

• α= 0.10 (10%) - political polling

The level appropriate for the current research topic can be 5% (0.05).

Step 3 - identify the test statistic- select formula for the right-tailed, one-sample t-test to compare a sample's mean. When the population standard deviation is unknown, the t-value is computed using the formula (X-M)/(S/ sqrt of N). The “descriptive analysis” statistics tool in Excel generates Sample Mean (X), Sample Variance (S), and Sample size (N) from the sample data. The null hypothesis or population mean (M) in a one-sample hypothesis test is the default theory mean value.

Step 4 - The t-value is plotted on the sampling distribution curve function, using an Excel formula-‘T-DIST to arrive at the p-value’ (on the assumption that null is true).

Step 5 - formulate a decision rule:

▪ p-value is the probability of finding an effect greater than the sample mean.

If p is larger than α, we cannot reject the null hypothesis; if it is smaller than α, we can reject it.

Calculate the p-value

○ If p-value is left tailed then: T.DIST(-t,n-1,1)

○ If p-value is right-tailed then:1- T.DIST (t,n-1,1)

○ If the p-value is two-tailed, then: 2* (1- T.DIST (t,n-1,1))

Step 6- Make a decision

Compare p-value to the significance level to reject or not on the following logic:

▪ p-value < significance level of 0.05 - H0 is rejected

▪ p-value > significance level of 0.05 - H0 is not rejected

D.3 Code for Data Wrangling and Feature Engineering for Survey Data in "R"

Loading the survey data into R and assigning object 'survey' to the

dataset. We also take a broad overview look of the survey data through the

summary function

```
```{r}

setwd("~/Desktop/R files - Research")

library(readr)

library(dplyr)

library(lubridate)

library(ggplot2)

library(tidyr)
```
```

library(patchwork)

survey <- read.csv("survey.csv")

summary(survey)

```

I. Data Cleaning and Feature Engineering

From the summary - we clean the Income column where some values have blank

answers and change it to "Prefer not to answer"

Change the blank answer category in 'Income' to 'Prefer not to answer'

```{r}

survey <- survey |>

  mutate(Income = if_else(Income == "", "Prefer not to answer", Income))

```
```

Data set before feature engineering:

```
summary(survey_clean)
```

```
 Respondents       C_Optimism     C_Gambler.Fallacy   C_Recency       C_Bounded.Rationality
Min.   :  1.0   Min.   :0.0000   Min.   :0.0000    Min.   :0.0000   Min.   :0.0000       
1st Qu.: 35.5   1st Qu.:0.0000   1st Qu.:0.0000    1st Qu.:0.0000   1st Qu.:0.0000       
Median : 70.0   Median :1.0000   Median :0.0000    Median :1.0000   Median :1.0000       
Mean   : 70.0   Mean   :0.5252   Mean   :0.1655    Mean   :0.5612   Mean   :0.5683       
3rd Qu.:104.5   3rd Qu.:1.0000   3rd Qu.:0.0000    3rd Qu.:1.0000   3rd Qu.:1.0000       
Max.   :139.0   Max.   :1.0000   Max.   :1.0000    Max.   :1.0000   Max.   :1.0000       
E_Loss.Averse     E_Status.Quo     E_Self.Attrb       E_Heard         C_OverOptimism  
Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000  
1st Qu.:1.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:1.0000   1st Qu.:1.0000  
Median :1.0000   Median :1.0000   Median :1.0000   Median :1.0000   Median :1.0000  
Mean   :0.7626   Mean   :0.6187   Mean   :0.6331   Mean   :0.7914   Mean   :0.9137  
3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000  
Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000  
C_Representativeness  C_Home.Bias        C_MenAcc       E_Disposition.Effect  E_SelfConrol   
Min.   :0.0000       Min.   :0.0000   Min.   :0.0000   Min.   :0.0000       Min.   :0.0000  
1st Qu.:1.0000       1st Qu.:1.0000   1st Qu.:0.0000   1st Qu.:0.0000       1st Qu.:0.0000  
Median :1.0000       Median :1.0000   Median :0.0000   Median :0.0000       Median :1.0000  
Mean   :0.7554       Mean   :0.9353   Mean   :0.2806   Mean   :0.3453       Mean   :0.5612  
3rd Qu.:1.0000       3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000       3rd Qu.:1.0000  
Max.   :1.0000       Max.   :1.0000   Max.   :1.0000   Max.   :1.0000       Max.   :1.0000  
E_Hindside.Bias  E_OverConfidence                 Gender              Age    
Min.   :0.0000   Min.   :0.0000   Female              : 30   18 - 35     :46  
1st Qu.:0.0000   1st Qu.:1.0000   Male                :108   36 - 50     :48  
Median :0.0000   Median :1.0000   Prefer not to answer:  1   50 and above:45  
Mean   :0.3165   Mean   :0.8273                                              
3rd Qu.:1.0000   3rd Qu.:1.0000                                              
Max.   :1.0000   Max.   :1.0000                                              
              Qualification                          Occupation                         Income  
Graduate             :41    Not listed above              : 3                             : 8  
High school or less  : 1    Own Business/ Self employed:27   10 to 25 Lakhs/year       :31  
Post Graduate or more:92    Professional                  :23   5 - 10 Laks/year          :23  
Undergraduate        : 5    Retired                       : 8   Below  5 Lakh/year        : 6  
                            Salaried                      :73   More than 25 Lakh/year:71  
                            Student                       : 5                              
            Trading.Exp  
0 - 3 years        :38  
3- 10 years        :44  
More than 10 years:57  
```

```{r}

# Renaming columns in the dataset

survey <- survey %>%
```

```
  rename(E_Hindsight.Bias = E_Hindsight.Bias)
survey <-survey %>%
  rename(E_Herd = E_Herd)
survey <- survey %>%
  rename(E_SelfControl = E_SelfConrol)

#Feature Engineering for Demographic Variables
#Clubbing levels for Qualification
survey$Qualification <- ifelse(survey$Qualification %in% c("High school or
less", "Undergraduate", "Graduate"), "Graduate and below",
survey$Qualification)
# Clubbing levels for Income
survey$Income <- ifelse(survey$Income %in% c("Below  5 Lakh/year", "5 - 10
Laks/year"), "Below 10 Lakhs", survey$Income)
#Occupation
survey$Occupation <- ifelse(survey$Occupation %in% c("Retired", "Not
listed above"), "Other", survey$Occupation)
survey <- survey %>%
```

filter(Gender != "Prefer not to answer")

survey <- survey %>%

filter(Occupation != "Student")

```
summary(survey_clean)
```

```
  Respondents       C_Optimism     C_Gambler.Fallacy   C_Recency      C_Bounded.Rationality E_Loss.Averse
 Min.   :  1.00   Min.   :0.0000   Min.   :0.0000    Min.   :0.0000   Min.   :0.0000        Min.   :0.0000
 1st Qu.: 35.00   1st Qu.:0.0000   1st Qu.:0.0000    1st Qu.:0.0000   1st Qu.:0.0000        1st Qu.:1.0000
 Median : 72.00   Median :1.0000   Median :0.0000    Median :1.0000   Median :1.0000        Median :1.0000
 Mean   : 70.81   Mean   :0.5414   Mean   :0.1729    Mean   :0.5564   Mean   :0.5789        Mean   :0.7669
 3rd Qu.:105.00   3rd Qu.:1.0000   3rd Qu.:0.0000    3rd Qu.:1.0000   3rd Qu.:1.0000        3rd Qu.:1.0000
 Max.   :139.00   Max.   :1.0000   Max.   :1.0000    Max.   :1.0000   Max.   :1.0000        Max.   :1.0000
  E_Status.Quo     E_Self.Attrb        E_Herd       C_OverOptimism   C_Representativeness  C_Home.Bias
 Min.   :0.0000   Min.   :0.0000   Min.   :0.000   Min.   :0.0000   Min.   :0.0000       Min.   :0.0000
 1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:1.000   1st Qu.:1.0000   1st Qu.:0.0000       1st Qu.:1.0000
 Median :1.0000   Median :1.0000   Median :1.000   Median :1.0000   Median :1.0000       Median :1.0000
 Mean   :0.6165   Mean   :0.6241   Mean   :0.797   Mean   :0.9248   Mean   :0.7444       Mean   :0.9474
 3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.000   3rd Qu.:1.0000   3rd Qu.:1.0000       3rd Qu.:1.0000
 Max.   :1.0000   Max.   :1.0000   Max.   :1.000   Max.   :1.0000   Max.   :1.0000       Max.   :1.0000
    C_MenAcc      E_Disposition.Effect E_SelfControl    E_Hindsight.Bias E_OverConfidence    Gender
 Min.   :0.0000   Min.   :0.0000       Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Female: 28
 1st Qu.:0.0000   1st Qu.:0.0000       1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:1.0000   Male  :105
 Median :0.0000   Median :0.0000       Median :1.0000   Median :0.0000   Median :1.0000
 Mean   :0.2857   Mean   :0.3534       Mean   :0.5639   Mean   :0.3233   Mean   :0.8421
 3rd Qu.:1.0000   3rd Qu.:1.0000       3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:1.0000
 Max.   :1.0000   Max.   :1.0000       Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
          Age                  Qualification                     Occupation                      Income
 18 - 35     :41   Graduate and below    :45   Other                      :11   10 to 25 Lakhs/year    :30
 36 - 50     :48   Post Graduate or more:88   Own Business/ Self employed:27   Below 10 Lakhs          :25
 50 and above:44                               Professional               :23   More than 25 Lakh/year:70
                                               Salaried                   :72   Prefer not to answer  : 8


            Trading.Exp
 0 - 3 years        :35
 3- 10 years        :42
 More than 10 years:56
```

```

From the summary we see that the demographic variables are read as an

incorrect data class of 'character', where it needs to be read as 'factor'
```

data class

1. Make a dataset survey_ftr that contains only the demographic variables

````
```{r}

library(dplyr)

survey_ftr <- survey |>

  select( c("Gender", "Age","Qualification",

"Occupation","Income","Trading.Exp")) #keep the variables that should be

factor

str(survey_ftr)

```
````

b. Seeing that they are currently of data class "character - chr", change

them to factor

````
```{r}

#changing chr to factor

survey_ftr[sapply(survey_ftr, is.character)] <-

lapply(survey_ftr[sapply(survey_ftr, is.character)],as.factor)

#check the variables' data class

str(survey_ftr)
````
````

```

Checking the bias variables

```{r}

survey_binary <- survey |>

  select( -c("Gender", "Age","Qualification",

"Occupation","Income","Trading.Exp")) #take out the variables that

shouldn't be numeric/binary

str(survey_binary)

```

The bias variables are all correctly assigned as 'integer' data class. We

now proceed to shift back the survey_ftr to the dataset.

```{r}

#adding back numerical variables to our dataframe

survey_clean <- cbind(survey_binary, survey_ftr)

#check our new dataset

str(survey_clean)

summary(survey_clean)

```
```

D.4 Survey Questionnaire

Q1. From 1999 to 2023, if the compounded annual growth of Nifty50 in India has been around 14%, what compounded annualised growth of Nifty50 do you predict in the year 2024?

- Well above 14%
- Above 14%
- Around 14%
- Below 14%

Q2: The results of a coin toss from the first 5 tosses, in order of sequence are:

1) Tails 2)Tails 3) Heads 4)Heads 5) Heads

What is the most likely outcome from the 6th toss of the coin?

- Tails, because law of average should catch up after 2 times Tails and 3 times Heads in first 5 tosses
- Heads, because the momentum is in favour of Heads
- Can be either Tales or Heads with equal likelihood
- Cannot predict with more than 50% accuracy

Q3. Which was the leading cause of human deaths in the world in 2023?

- Deaths due to wars between countries
- Heart Diseases
- COVID19
- None of the above

Q4. Do you think that the events of geo-political unrest, like in Russia - Ukraine, Israel - Iran... have impacted the Indian stock markets in a negative way in the last 3-5 years?

- Yes, otherwise Indian stock markets would have performed better than it actually did in the last 3-5 years
- No, geo-political unrests outside India do not impact Indian stock markets.

Q5. In a hypothetical situation, if you must choose an option, which option would you choose?

Option A: A sure loss of Rupees 7,250

Option B: 75% chance of losing Rupees 10,000, with 25% chance of losing nothing.

- Option A
- Option B

Q6. Assume that you get an opportunity to invest in a stock XYZ which can give you a return of 19% per year. Would you sell your existing stocks of ABC (which has been consistently giving you a 11% yearly returns) to invest in the XYZ stocks?

(Assume that the risk involved in the XYZ is 1.5 times more than the risk in ABC stocks)

- Yes, I will sell my ABC stocks to invest in XYZ stocks because of its better reward/risk ratio
- No, I will let not sell my performing ABC stocks to invest in a new XYZ stocks

Q7: Did you ever regret buying/selling a stock based on tips from any source/advisor?

- Yes
- No

Q8. If you have to buy a sweet box for your boss on the way to his house, which sweet shop would you buy it from?
A) shop which has many customers already waiting to buy the sweets
B) shop where there is no customer seen in the shop

(Assume that both the shops look equally good but you have no knowledge about the sweets in their shops)

- Shop A

- Shop B

Q9. Currently India is the 5th largest economy in the world in terms of GDP with USA at 27, China at 17.8, Germany at 4.4 Japan at 4.2 and India at 3.7 (in Trillion USD)

Do you think that India will become the 3rd largest economy in the world by 2030?

- Yes
- No

Q10. If you were a given a chance to select one player, which player would you pick for the Indian men's team for the upcoming T-20 world cup.

Player 1: who has a very good long-term track record in domestic cricket, but is currently out of form.

Player 2: who does not have a very good long-term record in domestic cricket, but he is in super form currently.

- Player 1
- Player 2

Q11. India is currently amongst the fastest growing countries in terms of GDP. Will India offer the best opportunity to grow investors' wealth in its stock market in the next 5 years?

- Yes
- No

Q12. Assume that you win a prize money of INR 10,000 in a game of Tambola/Housie/Bingo during your family holiday. How would you use this prize money?

Option1: Use it to pay for the regular expenses of the holiday so that I can save on the planned/budgeted expenses.

Option 2: Spend it on shopping for the family because the regular expenses of the holiday are already planned/budgeted for.

- Option 1
- Option 2

Q13. Assume that you bought 1000 shares of a company ABC for INR 12/share, expecting it to go up to INR 20/share in one year, based on its future growth plans. But within a month of your purchase, its price has fallen to INR 9/share. What would you do with the shares of ABC?

- Hold on to all the 1000 shares because its price may recover
- Sell the shares immediately partly/fully to reduce/minimise the losses
- Buy more to reduce my average purchase price.

- Research the cause of the drop before any action even if could take some time

Q14. Suppose you have a budget of INR 4 lakhs for an international holiday with your family. Your holiday planning agency gives you 2 options to choose from:

1) An exotic European Cruise holiday listed at INR 7 lakhs but available to you at a special discounted price of INR 5 Lakhs.

2) A regular holiday plan in Europe to fit into your budget of INR 4 Lakhs.

What option would you choose?

- The exotic cruise holiday option even at a price above my budget because such good discounts may not be available again
- The regular holiday option because it fits my budget

Q15. Suppose, you have been told by your friend about a stock that may give a 10% return on your investment within a month, but with a risk of loss of 5%.

What would you regret more?

Option 1: Buying the stock with the hope to get a 10% gains but ending up losing 5%.

OR

Option 2: Not buying the stocks with a fear of losing 5% but realizing after a month that stock price has gone up by 10%

- Option 1
- Option 2

Q16. Relative to other participants in the stock market, how good an analyst are you? (in terms of predicting the price movements in the Indian stock market).

- Better than 50% of the people who invest in stock markets
- Average
- Worse than 50% of the people who invest in stock markets

Demographic Questions:

Q17. What is your name?

Q18. What is your gender?

- Male

- Female
- Other
- Prefer not to answer

Q19. What is your age?

- Below 18
- 18-35
- 35-50
- 50 and above

Q20. What is your highest academic qualification?

- Post Graduate or more
- Graduate
- Undergraduate
- High school or less

Q21. What is you occupation?

- Own Business/ Self employed

- Salaried
- Professional
- Retired

Q22. What is your annual income range (in INR)

- Below 5 Lakh/year
- 5 - 10 Laks/year
- 10 to 25 Lakhs/year
- More than 25 Lakh/year

Q23. How long have you been investing/trading in stock markets either on your own or through a broker?

- 0-3 years
- 3-10 years
- More than 10 years
- Never

Q24: Your email id

D.5 Code for Statistical Analysis – Chi-Square and Linear Regressions in “R”

~~~~
#Chi-sq tests:

```{r}

# Install required library

#install.packages("vcd")

library(vcd)

# Convert continuous scores to High/Low categories

survey_clean$Cognitive_Category <- ifelse(survey_clean$Cognitive_Bias >

0.5, "High", "Low")

survey_clean$Emotional_Category <- ifelse(survey_clean$Emotional_Bias >

0.5, "High", "Low")

survey_clean$Overall_Category <- ifelse(survey_clean$Overall_Bias > 0.5,

"High", "Low")

# Define bias categories and demographics

bias_categories <- c("Cognitive_Category", "Emotional_Category",

"Overall_Category")
~~~~

```
demographics <- c("Gender", "Age", "Qualification", "Occupation",
"Income", "Trading.Exp")
# Initialize results storage
chi_sq_results <- list()
# Chi-Square Test for Bias Categories by Demographics
for (bias in bias_categories) {
  for (demo in demographics) {
    # Create a contingency table
    table_data <- table(survey_clean[[bias]], survey_clean[[demo]])
    # Perform Chi-Square test
    test_result <- chisq.test(table_data)
    # Calculate Cramér's V for significant results
    if (test_result$p.value < 0.05) {
      cramers_v <- assocstats(table_data)$cramer
      chi_sq_results[[paste(bias, demo, sep = "_")]] <- list(
        bias = bias,
        demographic = demo,
```

````
    p_value = test_result$p.value,

    cramers_v = cramers_v,

    observed = test_result$observed,

    expected = test_result$expected

)

   # Print significant results with strength of association

   cat(sprintf("\nSignificant Association Found:\n"))

   cat(sprintf("Bias: %s, Demographic: %s\n", bias, demo))

   cat(sprintf("p-value: %.4f, Cramér's V: %.3f\n",

test_result$p.value, cramers_v))

  }

} }

```

```{r}

#FOR INDIVIDUAL BIASES AND DEMOGRAPHICS

# Define bias columns and demographics
````

```
bias_columns <- colnames(survey_clean)[2:17]

demographics <- c("Gender", "Age", "Qualification", "Occupation",

"Income", "Trading.Exp")

# Initialize results storage

chi_sq_results <- list()

# Chi-Square Test for Bias Variables by Demographics

for (bias in bias_columns) {

  for (demo in demographics) {

    # Create a contingency table

    table_data <- table(survey_clean[[bias]], survey_clean[[demo]])

    # Perform Chi-Square test

    test_result <- chisq.test(table_data)

    # Calculate Cramér's V for significant results

    if (test_result$p.value < 0.05) {

      cramers_v <- assocstats(table_data)$cramer

      chi_sq_results[[paste(bias, demo, sep = "_")]] <- list(

        bias = bias,
```

````
        demographic = demo,
        p_value = test_result$p.value,
        cramers_v = cramers_v,
        observed = test_result$observed,
        expected = test_result$expected
)
      # Print significant results with strength of association
      cat(sprintf("\nSignificant Association Found:\n"))
      cat(sprintf("Bias: %s, Demographic: %s\n", bias, demo))
      cat(sprintf("p-value: %.4f, Cramér's V: %.3f\n",
test_result$p.value, cramers_v))
    }
} }
```
#REGRESSION ANALYSIS
```{r}
````

````
# Remove the first column (Respondent)

survey_lr <- survey_clean[, -1]

```

```{r}

# Define bias scores

bias_scores <- c("Overall_Bias", "Cognitive_Bias", "Emotional_Bias")

# Run linear regressions

linear_results <- list()

for (bias in bias_scores) {

  # Formula: Bias Score ~ Demographics

  formula <- as.formula(paste(bias, "~", paste(demographics, collapse = "
+ ")))

  # Linear regression model

  model <- lm(formula, data = survey_lr)

  summary_model <- summary(model)

  # Store results
````

  linear_results[[bias]] <- summary_model

  # Print summary

  cat(sprintf("\nLinear Regression Results for %s:\n", bias))

  print(summary_model)

} ```

#LR with interactive terms:

```{r}

# Interaction terms to include

interaction_terms <- c("Age:Gender", "Occupation:Income",

"Gender:Trading.Exp", "Trading.Exp:Income")

# Run linear regression models with interaction terms

linear_interactive_results <- list()

for (bias in bias_scores) {

  # Create formula with interaction terms

  formula <- as.formula(paste(bias, "~", paste(c(demographics,

interaction_terms), collapse = " + ")))
```

```
  # Fit the linear regression model
  model <- lm(formula, data = survey_lr)
  summary_model <- summary(model)
  # Store results
  linear_interactive_results[[bias]] <- summary_model
  # Print summary
  cat(sprintf("\nLinear Regression Results for %s (with interactions):\n",
bias))
  print(summary_model)
```

D.6 Results for Chi-Square tests and Cramer's V tests in "R"

Significant Association Found:

Bias: Emotional_Category, Demographic: Age

p-value: 0.0366, Cramér's V: 0.223

Significant Association Found:

Bias: C_Gambler.Fallacy, Demographic: Age

p-value: 0.0485, Cramér's V: 0.213

Significant Association Found:

Bias: C_Recency, Demographic: Age

p-value: 0.0026, Cramér's V: 0.299

Significant Association Found:

Bias: C_Recency, Demographic: Income

p-value: 0.0105, Cramér's V: 0.291

Significant Association Found:

Bias: E_Status.Quo, Demographic: Occupation

p-value: 0.0204, Cramér's V: 0.271

Significant Association Found:

Bias: E_Herd, Demographic: Trading.Exp

p-value: 0.0265, Cramér's V: 0.234

Significant Association Found:

Bias: C_OverOptimism, Demographic: Age

p-value: 0.0295, Cramér's V: 0.230

Significant Association Found:

Bias: C_OverOptimism, Demographic: Trading.Exp

p-value: 0.0048, Cramér's V: 0.284

Significant Association Found:

Bias: C_Representativeness, Demographic: Age

p-value: 0.0004, Cramér's V: 0.341

Significant Association Found:

Bias: C_Representativeness, Demographic: Occupation

p-value: 0.0325, Cramér's V: 0.257

Significant Association Found:

Bias: C_Representativeness, Demographic: Income

p-value: 0.0052, Cramér's V: 0.310

Significant Association Found:

Bias: E_Disposition.Effect, Demographic: Qualification

p-value: 0.0383, Cramér's V: 0.196

Significant Association Found:

Bias: E_SelfControl, Demographic: Income

p-value: 0.0062, Cramér's V: 0.305

Significant Association Found:

Bias: E_Hindsight.Bias, Demographic: Age

p-value: 0.0493, Cramér's V: 0.213

Significant Association Found:

Bias: E_Hindsight.Bias, Demographic: Income

p-value: 0.0403, Cramér's V: 0.250

D.7 Results of Linear Regression for Group Biases and Demographic Profiles in "R"

a. Linear Regression Results for Overall_Bias:

```
Call:
lm(formula = formula, data = survey_lr)

Residuals:
      Min        1Q    Median        3Q       Max
-0.283990 -0.065690  0.002598  0.073667  0.282757

Coefficients:
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                            0.657867   0.057930  11.356   <2e-16 ***
GenderMale                            -0.054143   0.028469  -1.902   0.0596 .
Age36 - 50                             0.054121   0.033455   1.618   0.1083
Age50 and above                        0.006574   0.037546   0.175   0.8613
```

```
QualificationPost Graduate or more     0.020184   0.025688   0.786   0.4336

OccupationOwn Business/ Self employed -0.007233   0.047369  -0.153   0.8789

OccupationProfessional               -0.057921   0.048084  -1.205   0.2307

OccupationSalaried                   -0.018849   0.046095  -0.409   0.6833

IncomeBelow 10 Lakhs                 -0.033256   0.034882  -0.953   0.3423

IncomeMore than 25 Lakh/year         -0.014145   0.030362  -0.466   0.6422

IncomePrefer not to answer           -0.111703   0.053491  -2.088   0.0389 *

Trading.Exp3- 10 years                0.012326   0.030597   0.403   0.6878

Trading.ExpMore than 10 years        -0.022634   0.033832  -0.669   0.5048

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.1256 on 120 degrees of freedom

Multiple R-squared:  0.1128, Adjusted R-squared:  0.0241

F-statistic: 1.272 on 12 and 120 DF,  p-value: 0.2441
```

b. Linear Regression Results for Cognitive_Bias:

```
Call:

lm(formula = formula, data = survey_lr)
```

```
Residuals:

    Min      1Q  Median      3Q     Max

-0.4413 -0.0959  0.0076  0.1454  0.3482



Coefficients:

                                       Estimate Std. Error t value Pr(>|t|)

(Intercept)                            0.611689   0.080056   7.641 5.85e-12 ***

GenderMale                            -0.057204   0.039342  -1.454    0.149

Age36 - 50                             0.018009   0.046232   0.390    0.698

Age50 and above                        0.000882   0.051886   0.017    0.986

QualificationPost Graduate or more     0.021532   0.035499   0.607    0.545

OccupationOwn Business/ Self employed  0.062946   0.065462   0.962    0.338

OccupationProfessional                 0.020969   0.066450   0.316    0.753

OccupationSalaried                     0.045785   0.063700   0.719    0.474

IncomeBelow 10 Lakhs                  -0.055503   0.048205  -1.151    0.252

IncomeMore than 25 Lakh/year          -0.052379   0.041959  -1.248    0.214

IncomePrefer not to answer            -0.093811   0.073922  -1.269    0.207

Trading.Exp3- 10 years                 0.029967   0.042284   0.709    0.480

Trading.ExpMore than 10 years         -0.001404   0.046754  -0.030    0.976

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.1736 on 120 degrees of freedom

Multiple R-squared:  0.0618, Adjusted R-squared:  -0.03202

F-statistic: 0.6588 on 12 and 120 DF,  p-value: 0.7875
```

c. Linear Regression Results for Emotional_Bias:

```
Call:

lm(formula = formula, data = survey_lr)


Residuals:

     Min       1Q   Median       3Q      Max

-0.38940 -0.08688  0.01841  0.09396  0.39291


Coefficients:

                                       Estimate Std. Error t value Pr(>|t|)

(Intercept)                            0.704045   0.074303   9.475 3.06e-16 ***

GenderMale                            -0.051083   0.036515  -1.399   0.1644

Age36 - 50                             0.090234   0.042910   2.103   0.0376 *

Age50 and above                        0.012266   0.048158   0.255   0.7994

QualificationPost Graduate or more     0.018836   0.032948   0.572   0.5686

OccupationOwn Business/ Self employed -0.077413   0.060758  -1.274   0.2051
```

```
OccupationProfessional               -0.136811   0.061675  -2.218   0.0284 *

OccupationSalaried                   -0.083483   0.059123  -1.412   0.1605

IncomeBelow 10 Lakhs                 -0.011009   0.044741  -0.246   0.8061

IncomeMore than 25 Lakh/year          0.024090   0.038943   0.619   0.5374

IncomePrefer not to answer           -0.129596   0.068610  -1.889   0.0613 .

Trading.Exp3- 10 years               -0.005313   0.039245  -0.135   0.8925

Trading.ExpMore than 10 years        -0.043864   0.043394  -1.011   0.3141

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1



Residual standard error: 0.1612 on 120 degrees of freedom

Multiple R-squared:  0.1376, Adjusted R-squared:  0.05139

F-statistic: 1.596 on 12 and 120 DF,  p-value: 0.1015
```

d. Linear Regression Results for Overall_Bias (with interactions):

```
Call:

lm(formula = formula, data = survey_lr)



Residuals:

      Min        1Q    Median        3Q       Max

-0.252342 -0.067214 -0.000292  0.069697  0.249722
```

Coefficients: (1 not defined because of singularities)

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.775239	0.111096	6.978	3.08e-10	***
GenderMale	-0.106593	0.055903	-1.907	0.05937	.
Age36 - 50	-0.114300	0.083592	-1.367	0.17452	
Age50 and above	-0.244523	0.088312	-2.769	0.00668	**
QualificationPost Graduate or more	0.028672	0.026944	1.064	0.28978	
OccupationOwn Business/ Self employed	-0.241081	0.112094	-2.151	0.03386	*
OccupationProfessional	-0.052238	0.106636	-0.490	0.62528	
OccupationSalaried	-0.114069	0.101033	-1.129	0.26153	
IncomeBelow 10 Lakhs	-0.176094	0.147652	-1.193	0.23578	
IncomeMore than 25 Lakh/year	-0.049731	0.128986	-0.386	0.70063	
IncomePrefer not to answer	-0.026008	0.150334	-0.173	0.86300	
Trading.Exp3- 10 years	0.089122	0.082254	1.083	0.28114	
Trading.ExpMore than 10 years	0.176747	0.100704	1.755	0.08224	.
GenderMale:Age36 - 50	0.147676	0.088302	1.672	0.09751	.
GenderMale:Age50 and above	0.216551	0.092835	2.333	0.02163	*
OccupationOwn Business/ Self employed:IncomeBelow 10 Lakhs	0.368876	0.153893	2.397	0.01835	*
OccupationProfessional:IncomeBelow 10 Lakhs	0.030590	0.154678	0.198	0.84362	
OccupationSalaried:IncomeBelow 10 Lakhs	0.125710	0.142670	0.881	0.38032	
OccupationOwn Business/ Self employed:IncomeMore than 25 Lakh/year	0.282321	0.130824	2.158	0.03327	*
OccupationProfessional:IncomeMore than 25 Lakh/year	-0.007211	0.129226	-0.056	0.95561	
OccupationSalaried:IncomeMore than 25 Lakh/year	0.129032	0.119139	1.083	0.28135	

```
OccupationOwn Business/ Self employed:IncomePrefer not to answer   -0.026558   0.198861  -0.134  0.89402

OccupationProfessional:IncomePrefer not to answer                  -0.013484   0.154651  -0.087  0.93069

OccupationSalaried:IncomePrefer not to answer                       0.070270   0.197985   0.355  0.72338

GenderMale:Trading.Exp3- 10 years                                  -0.091634   0.084599  -1.083  0.28129

GenderMale:Trading.ExpMore than 10 years                           -0.144258   0.088696  -1.626  0.10694

IncomeBelow 10 Lakhs:Trading.Exp3- 10 years                         0.050890   0.086255   0.590  0.55650

IncomeMore than 25 Lakh/year:Trading.Exp3- 10 years                -0.025336   0.075608  -0.335  0.73824

IncomePrefer not to answer:Trading.Exp3- 10 years                         NA         NA      NA       NA

IncomeBelow 10 Lakhs:Trading.ExpMore than 10 years                  0.053625   0.096057   0.558  0.57789

IncomeMore than 25 Lakh/year:Trading.ExpMore than 10 years         -0.098703   0.082514  -1.196  0.23439

IncomePrefer not to answer:Trading.ExpMore than 10 years           -0.229990   0.138133  -1.665  0.09898 .

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1



Residual standard error: 0.1205 on 102 degrees of freedom

Multiple R-squared:  0.3065, Adjusted R-squared:  0.1025

F-statistic: 1.502 on 30 and 102 DF,  p-value: 0.06915
```

e. Linear Regression Results for Cognitive_Bias (with interactions):

```
Call:

lm(formula = formula, data = survey_lr)
```

```
Residuals:

     Min       1Q   Median       3Q      Max

-0.39171 -0.09898  0.01445  0.08980  0.39894


Coefficients: (1 not defined because of singularities)

                                                              Estimate Std. Error t value Pr(>|t|)

(Intercept)                                                    0.79645    0.15695   5.075 1.75e-06 ***

GenderMale                                                    -0.10110    0.07898  -1.280  0.20341

Age36 - 50                                                    -0.20157    0.11809  -1.707  0.09088 .

Age50 and above                                               -0.34585    0.12476  -2.772  0.00662 **

QualificationPost Graduate or more                             0.03357    0.03806   0.882  0.37986

OccupationOwn Business/ Self employed                         -0.23633    0.15836  -1.492  0.13869

OccupationProfessional                                        -0.02592    0.15065  -0.172  0.86375

OccupationSalaried                                            -0.11365    0.14273  -0.796  0.42775

IncomeBelow 10 Lakhs                                          -0.35806    0.20859  -1.717  0.08910 .

IncomeMore than 25 Lakh/year                                  -0.14679    0.18222  -0.806  0.42238

IncomePrefer not to answer                                    -0.02335    0.21238  -0.110  0.91267

Trading.Exp3- 10 years                                         0.18441    0.11620   1.587  0.11561

Trading.ExpMore than 10 years                                  0.21730    0.14227   1.527  0.12975

GenderMale:Age36 - 50                                          0.19024    0.12475   1.525  0.13035

GenderMale:Age50 and above                                     0.31573    0.13115   2.407  0.01786 *

OccupationOwn Business/ Self employed:IncomeBelow 10 Lakhs     0.51654    0.21741   2.376  0.01937 *

OccupationProfessional:IncomeBelow 10 Lakhs                    0.17025    0.21852   0.779  0.43772
```

```
OccupationSalaried:IncomeBelow 10 Lakhs                             0.25350    0.20155   1.258  0.21136

OccupationOwn Business/ Self employed:IncomeMore than 25 Lakh/year  0.35929    0.18482   1.944  0.05465 .

OccupationProfessional:IncomeMore than 25 Lakh/year                 0.03838    0.18256   0.210  0.83390

OccupationSalaried:IncomeMore than 25 Lakh/year                     0.21124    0.16831   1.255  0.21232

OccupationOwn Business/ Self employed:IncomePrefer not to answer   -0.06068    0.28093  -0.216  0.82944

OccupationProfessional:IncomePrefer not to answer                   0.03005    0.21848   0.138  0.89086

OccupationSalaried:IncomePrefer not to answer                       0.04729    0.27970   0.169  0.86607

GenderMale:Trading.Exp3- 10 years                                  -0.19863    0.11951  -1.662  0.09959 .

GenderMale:Trading.ExpMore than 10 years                           -0.21182    0.12530  -1.690  0.09399 .

IncomeBelow 10 Lakhs:Trading.Exp3- 10 years                         0.11948    0.12185   0.981  0.32915

IncomeMore than 25 Lakh/year:Trading.Exp3- 10 years                -0.03784    0.10681  -0.354  0.72390

IncomePrefer not to answer:Trading.Exp3- 10 years                        NA         NA      NA       NA

IncomeBelow 10 Lakhs:Trading.ExpMore than 10 years                  0.13112    0.13570   0.966  0.33623

IncomeMore than 25 Lakh/year:Trading.ExpMore than 10 years         -0.06991    0.11657  -0.600  0.55001

IncomePrefer not to answer:Trading.ExpMore than 10 years           -0.19618    0.19514  -1.005  0.31713

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 0.1702 on 102 degrees of freedom

Multiple R-squared:  0.2335, Adjusted R-squared:  0.008103

F-statistic: 1.036 on 30 and 102 DF,  p-value: 0.4311
```

f. Linear Regression Results for Emotional_Bias (with interactions):

```
Call:

lm(formula = formula, data = survey_lr)



Residuals:

     Min       1Q   Median       3Q      Max

-0.41331 -0.07435  0.00568  0.09454  0.35828



Coefficients: (1 not defined because of singularities)

                                              Estimate Std. Error t value Pr(>|t|)

(Intercept)                                   0.754027   0.152302   4.951 2.93e-06 ***

GenderMale                                   -0.112089   0.076638  -1.463    0.147

Age36 - 50                                   -0.027026   0.114597  -0.236    0.814

Age50 and above                              -0.143196   0.121067  -1.183    0.240

QualificationPost Graduate or more            0.023773   0.036938   0.644    0.521

OccupationOwn Business/ Self employed        -0.245833   0.153671  -1.600    0.113

OccupationProfessional                       -0.078558   0.146188  -0.537    0.592

OccupationSalaried                           -0.114492   0.138507  -0.827    0.410

IncomeBelow 10 Lakhs                          0.005867   0.202417   0.029    0.977

IncomeMore than 25 Lakh/year                  0.047325   0.176828   0.268    0.790

IncomePrefer not to answer                   -0.028665   0.206095  -0.139    0.890

Trading.Exp3- 10 years                       -0.006166   0.112763  -0.055    0.957

Trading.ExpMore than 10 years                 0.136191   0.138056   0.986    0.326

GenderMale:Age36 - 50                         0.105114   0.121054   0.868    0.387

GenderMale:Age50 and above                    0.117374   0.127268   0.922    0.359
```

OccupationOwn Business/ Self employed:IncomeBelow 10 Lakhs	0.221218	0.210973	1.049	0.297
OccupationProfessional:IncomeBelow 10 Lakhs	-0.109070	0.212049	-0.514	0.608
OccupationSalaried:IncomeBelow 10 Lakhs	-0.002081	0.195587	-0.011	0.992
OccupationOwn Business/ Self employed:IncomeMore than 25 Lakh/year	0.205351	0.179348	1.145	0.255
OccupationProfessional:IncomeMore than 25 Lakh/year	-0.052802	0.177157	-0.298	0.766
OccupationSalaried:IncomeMore than 25 Lakh/year	0.046823	0.163328	0.287	0.775
OccupationOwn Business/ Self employed:IncomePrefer not to answer	0.007560	0.272620	0.028	0.978
OccupationProfessional:IncomePrefer not to answer	-0.057022	0.212012	-0.269	0.789
OccupationSalaried:IncomePrefer not to answer	0.093252	0.271419	0.344	0.732
GenderMale:Trading.Exp3- 10 years	0.015360	0.115977	0.132	0.895
GenderMale:Trading.ExpMore than 10 years	-0.076693	0.121594	-0.631	0.530
IncomeBelow 10 Lakhs:Trading.Exp3- 10 years	-0.017701	0.118248	-0.150	0.881
IncomeMore than 25 Lakh/year:Trading.Exp3- 10 years	-0.012837	0.103651	-0.124	0.902
IncomePrefer not to answer:Trading.Exp3- 10 years	NA	NA	NA	NA
IncomeBelow 10 Lakhs:Trading.ExpMore than 10 years	-0.023867	0.131686	-0.181	0.857
IncomeMore than 25 Lakh/year:Trading.ExpMore than 10 years	-0.127495	0.113119	-1.127	0.262
IncomePrefer not to answer:Trading.ExpMore than 10 years	-0.263805	0.189367	-1.393	0.167

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

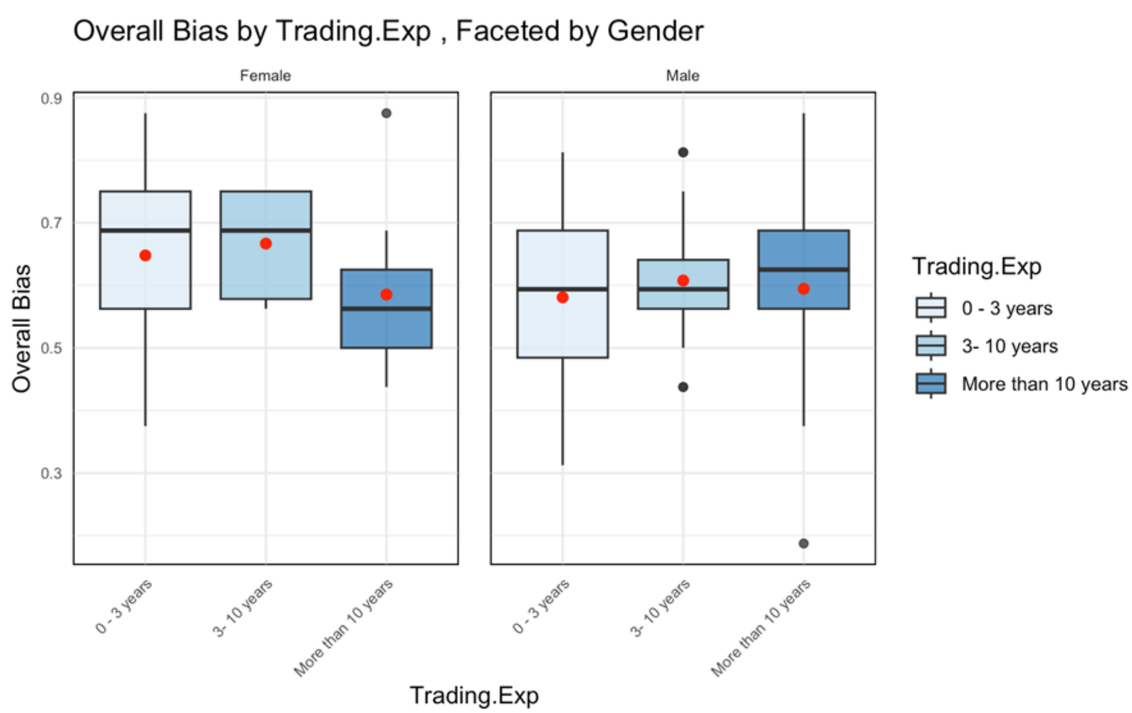
Residual standard error: 0.1652 on 102 degrees of freedom

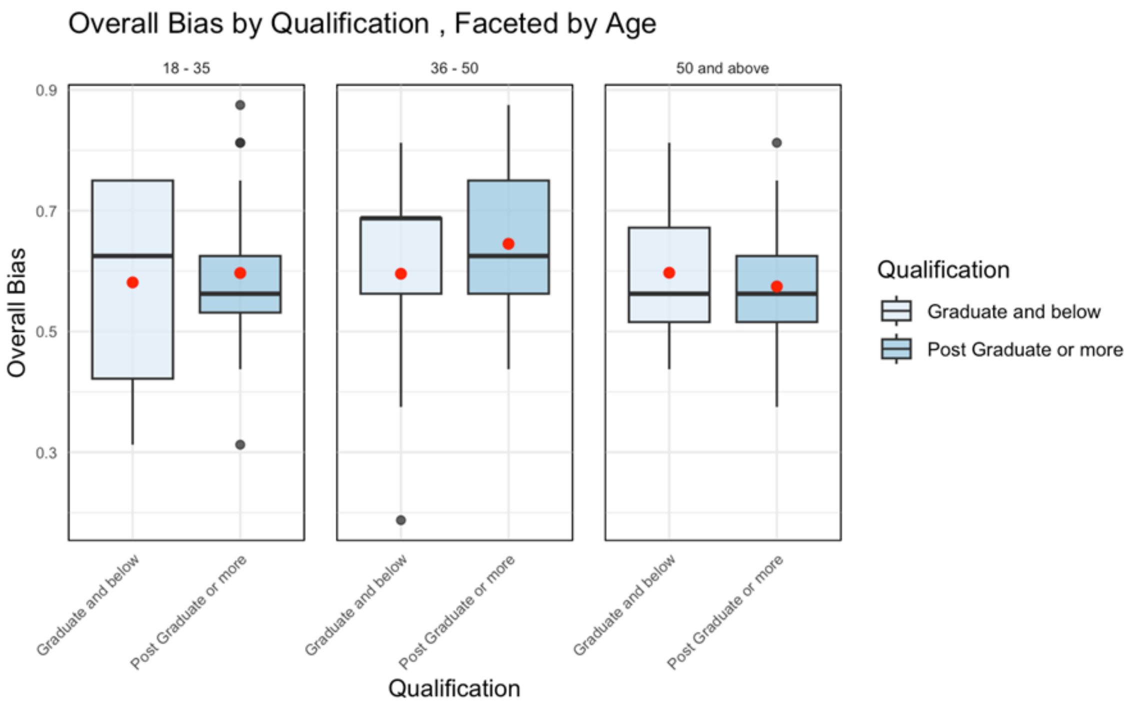
Multiple R-squared: 0.2299, Adjusted R-squared: 0.003345

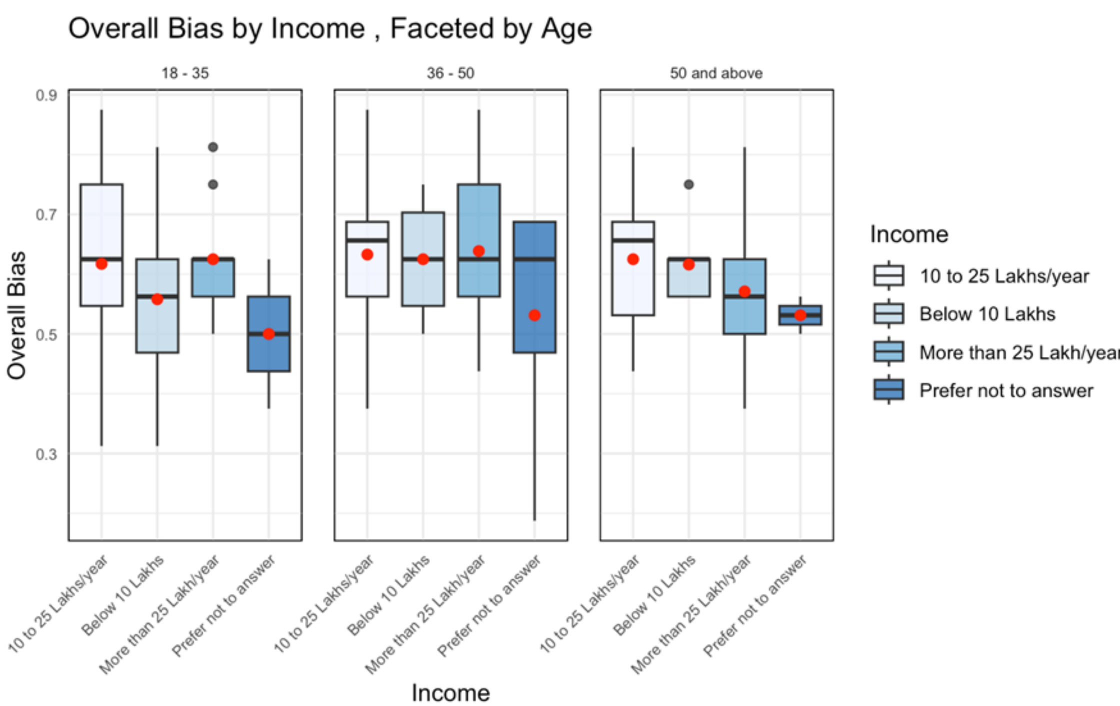
F-statistic: 1.015 on 30 and 102 DF, p-value: 0.4589

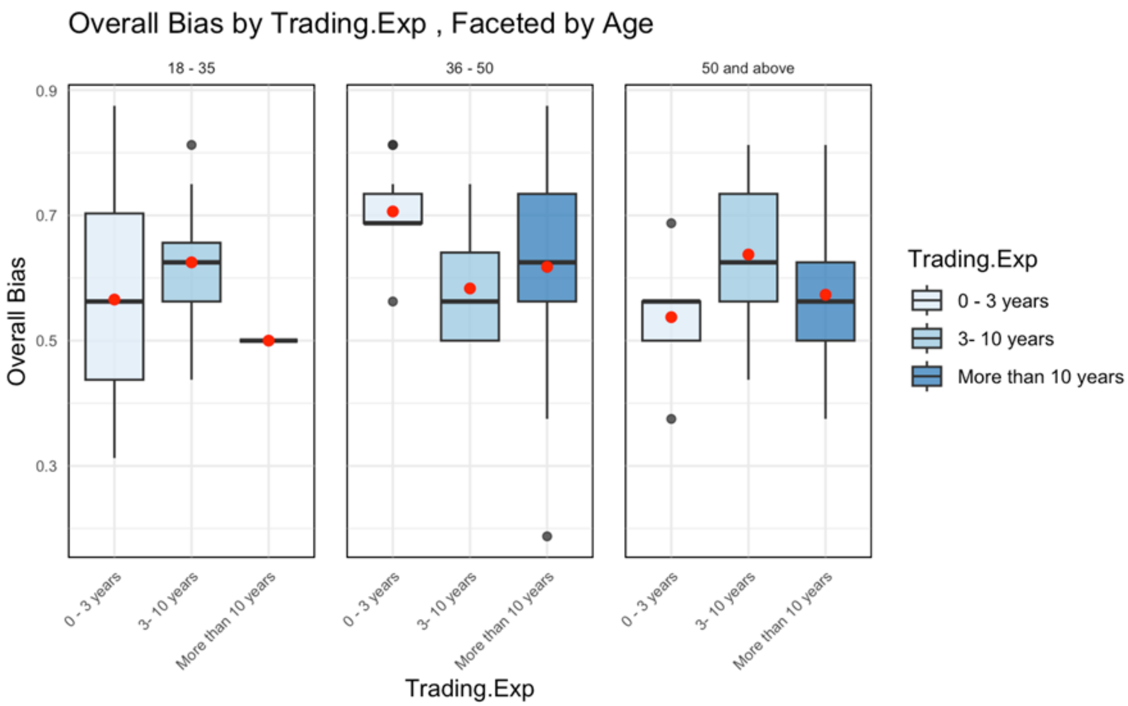
APPENDIX E

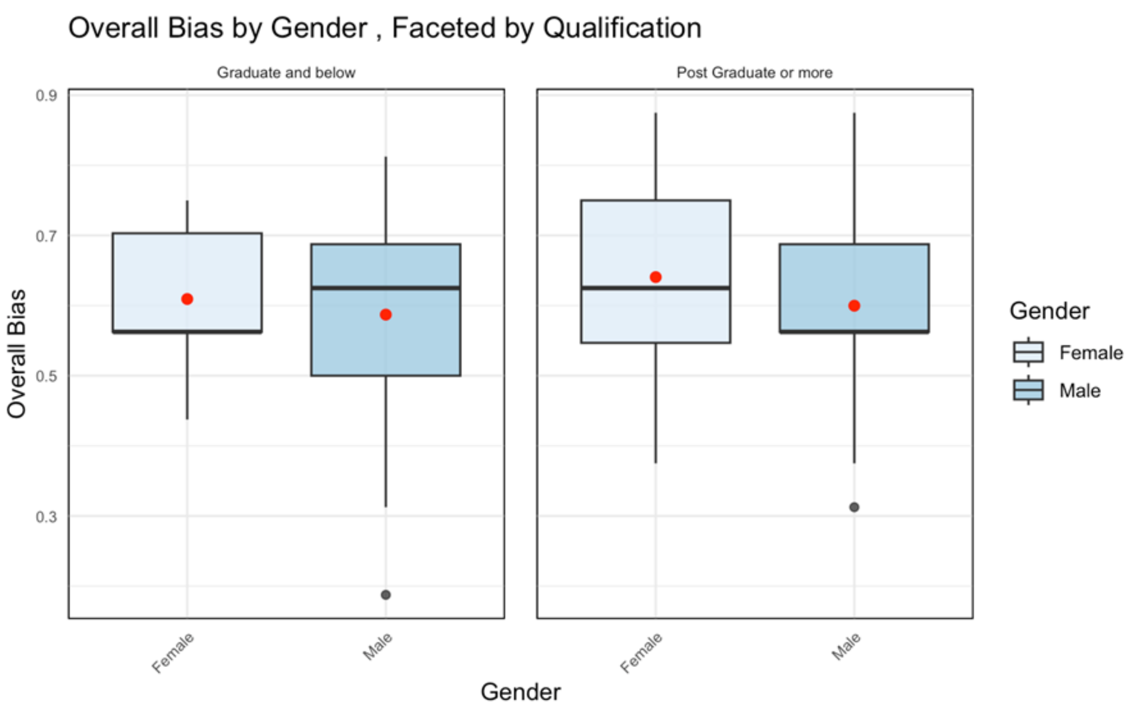
ADDITIONAL DESCRIPTIVE DEMOGRAPHIC ANALYSIS OF INVESTORS

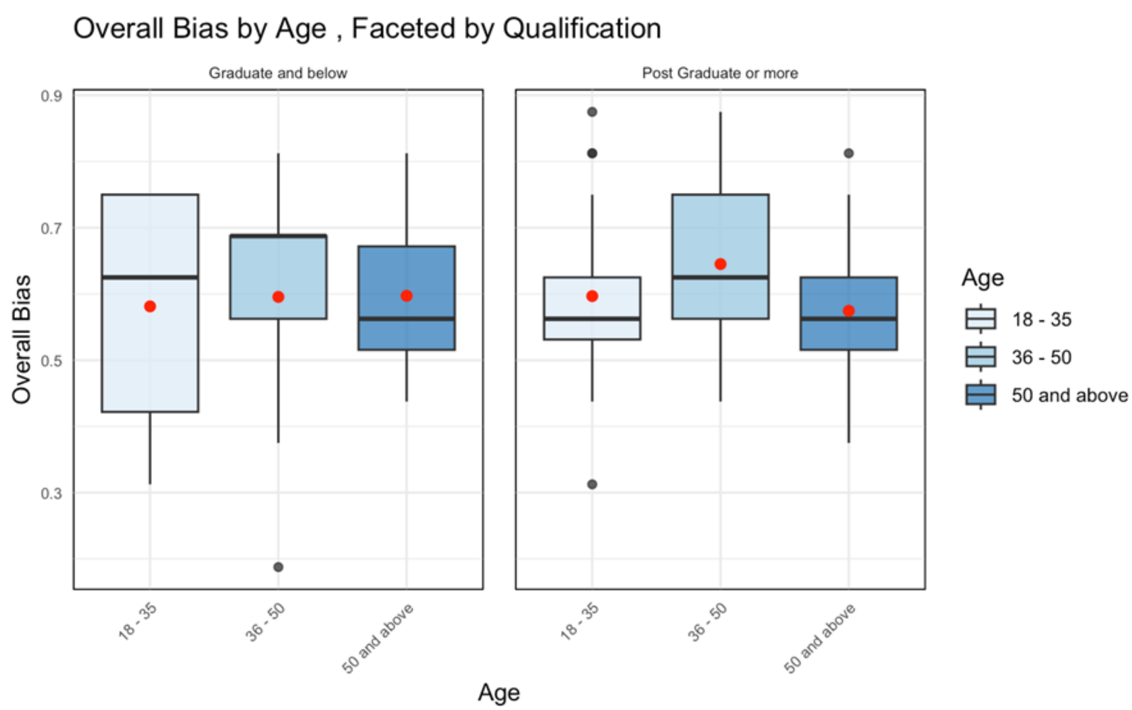



Overall Bias by Qualification , Faceted by Age
18 - 35
36 - 50
50 and above
Overall Bias
0.9
0.7
0.5
0.3
Graduate and below
Post Graduate or more
Qualification
Qualification
Graduate and below
Post Graduate or more

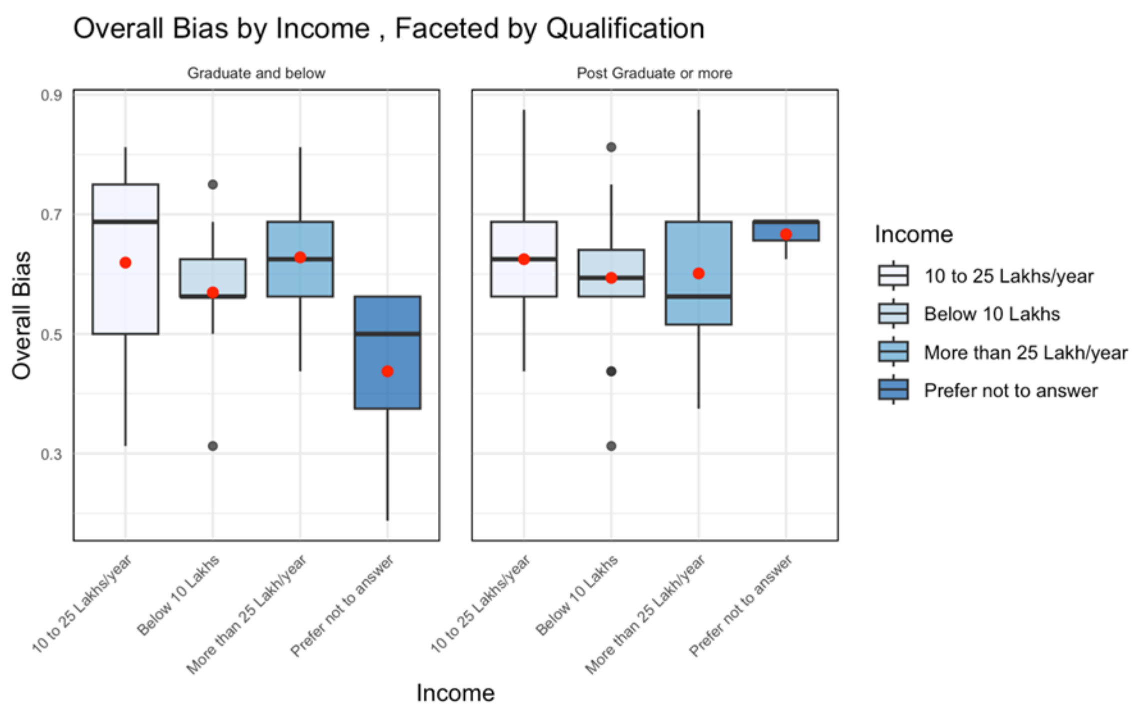

Overall Bias by Income , Faceted by Age
18 - 35
36 - 50
50 and above
Overall Bias
0.9
0.7
0.5
0.3
10 to 25 Lakhs/year
Below 10 Lakhs
More than 25 Lakh/year
Prefer not to answer
Income
Income
10 to 25 Lakhs/year
Below 10 Lakhs
More than 25 Lakh/year
Prefer not to answer


Overall Bias by Trading.Exp , Faceted by Age
18 - 35
36 - 50
50 and above
Overall Bias
0.9
0.7
0.5
0.3
0 - 3 years
3- 10 years
More than 10 years
Trading.Exp
Trading.Exp
0 - 3 years
3- 10 years
More than 10 years

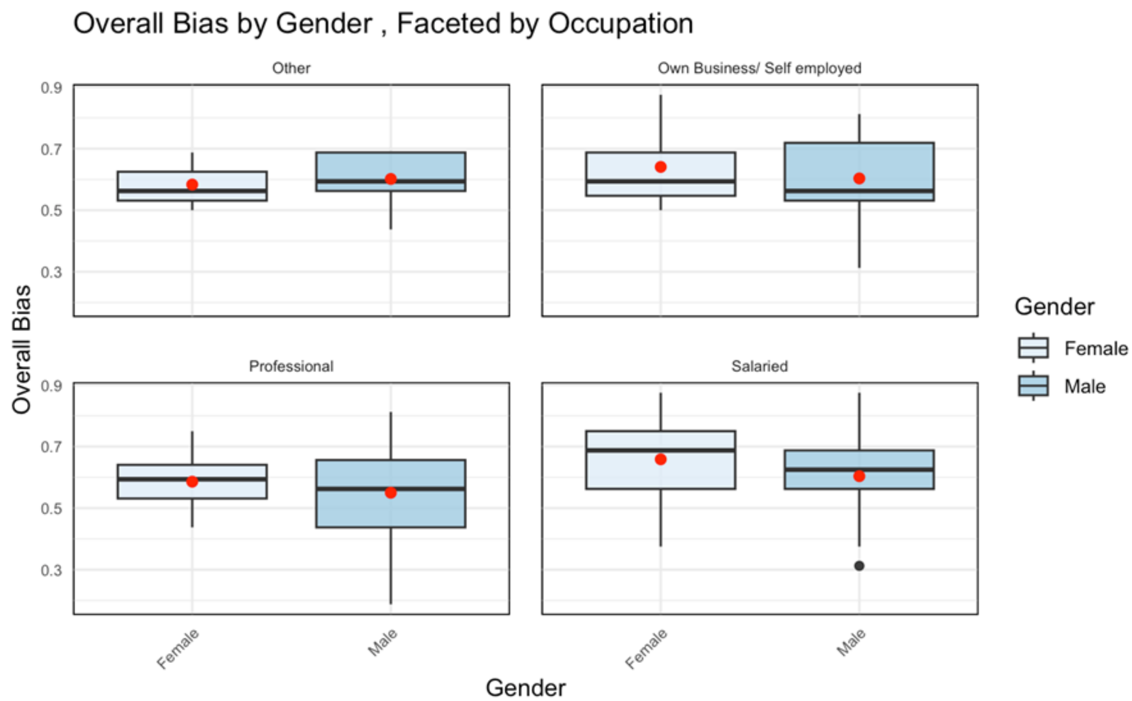

Overall Bias by Gender , Faceted by Qualification
Graduate and below
Post Graduate or more
Overall Bias
0.9
0.7
0.5
0.3
Female
Male
Gender
Gender
Female
Male

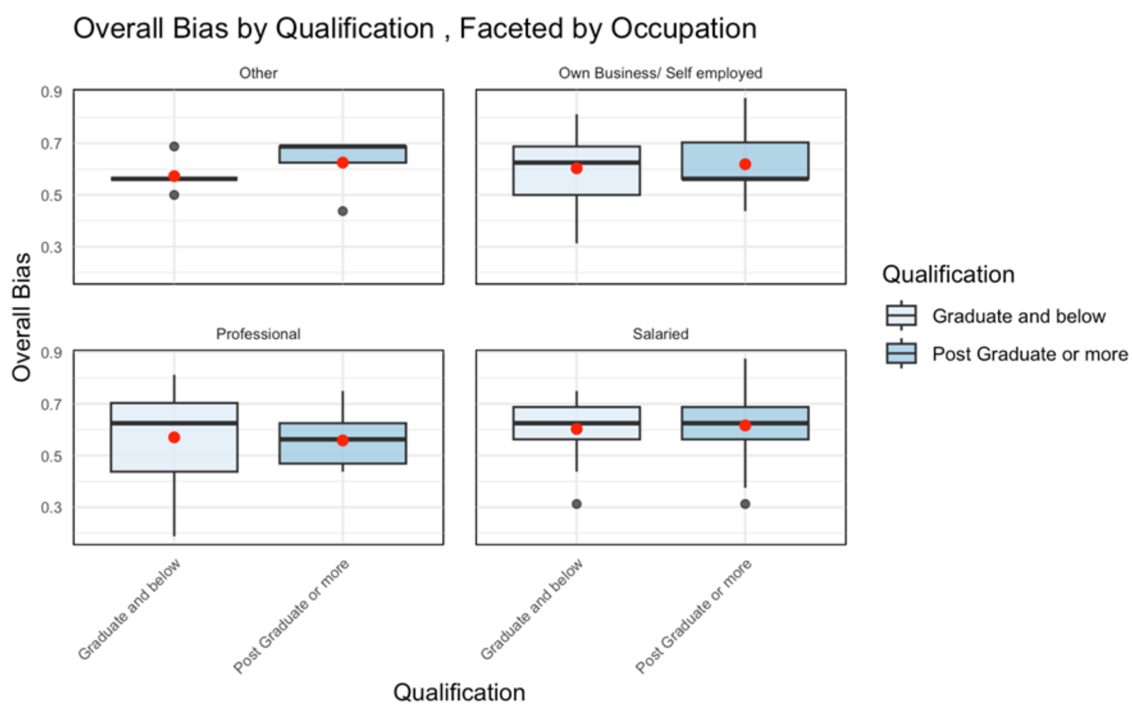

Overall Bias by Age , Faceted by Qualification
Graduate and below
Post Graduate or more
0.9
0.7
0.5
0.3
Overall Bias
18 - 35
36 - 50
50 and above
Age
Age
18 - 35
36 - 50
50 and above

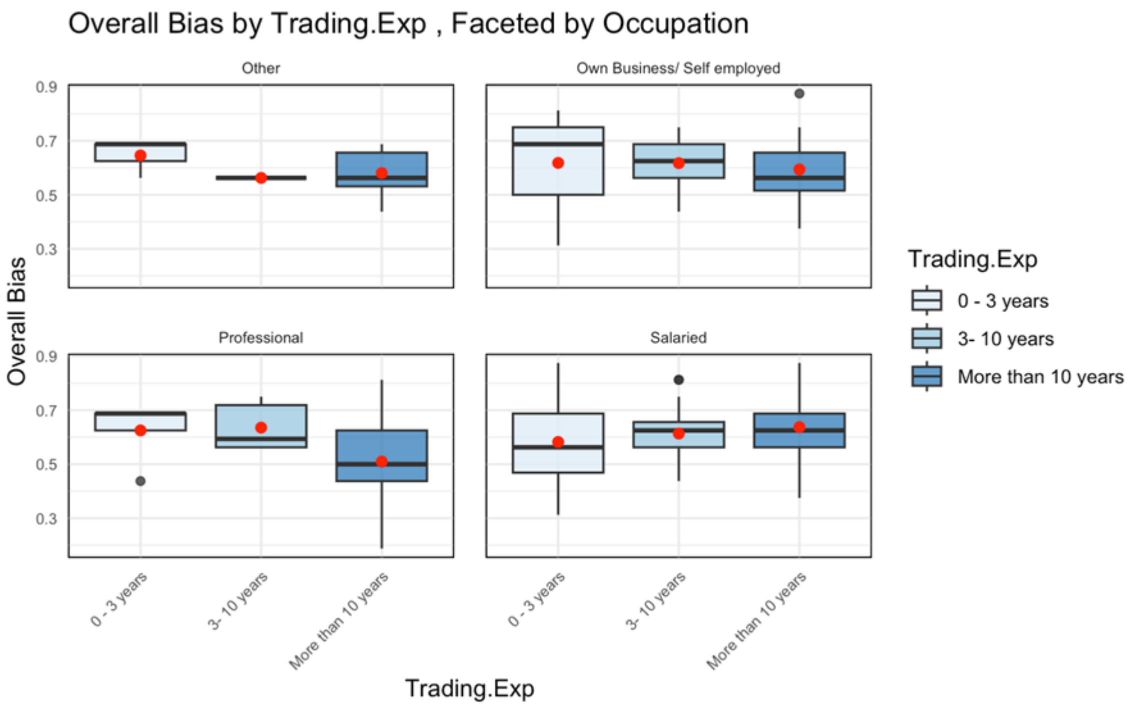

Overall Bias by Occupation , Faceted by Qualification
Graduate and below
Post Graduate or more
0.9
0.7
0.5
0.3
Overall Bias
Other
Own Business/ Self employed
Professional
Salaried
Occupation
Occupation
Other
Own Business/ Self employed
Professional
Salaried

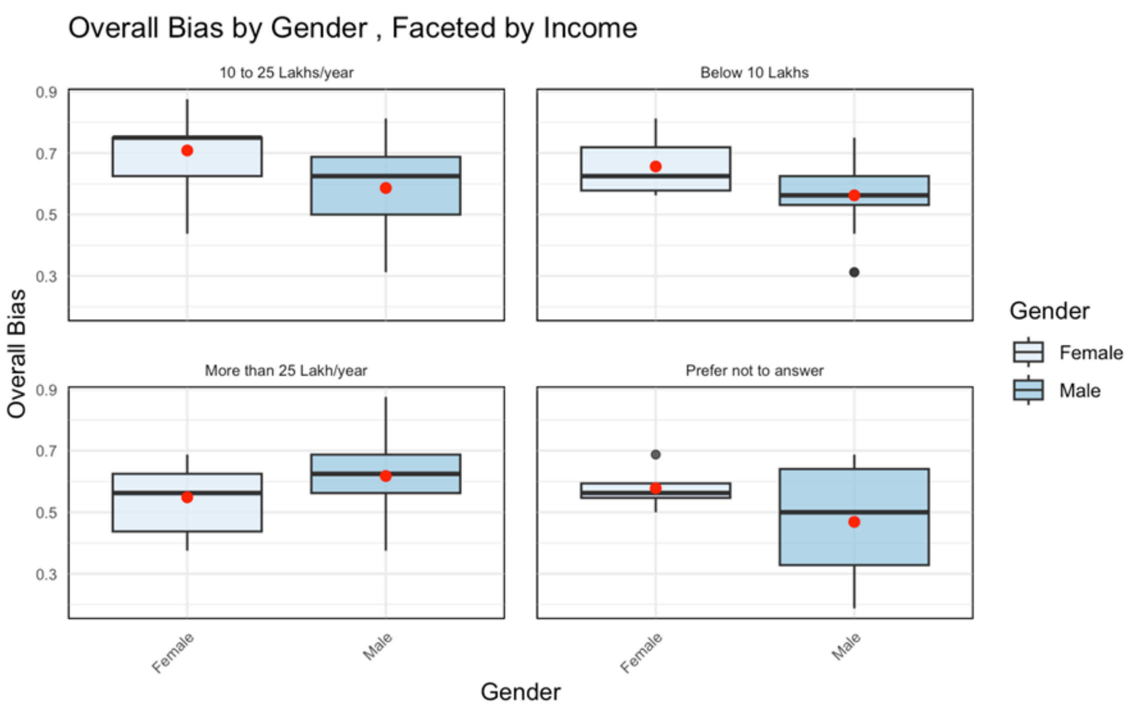

Overall Bias by Income , Faceted by Qualification
Graduate and below
Post Graduate or more
0.9
0.7
0.5
0.3
Overall Bias
10 to 25 Lakhs/year
Below 10 Lakhs
More than 25 Lakh/year
Prefer not to answer
Income
Income
10 to 25 Lakhs/year
Below 10 Lakhs
More than 25 Lakh/year
Prefer not to answer

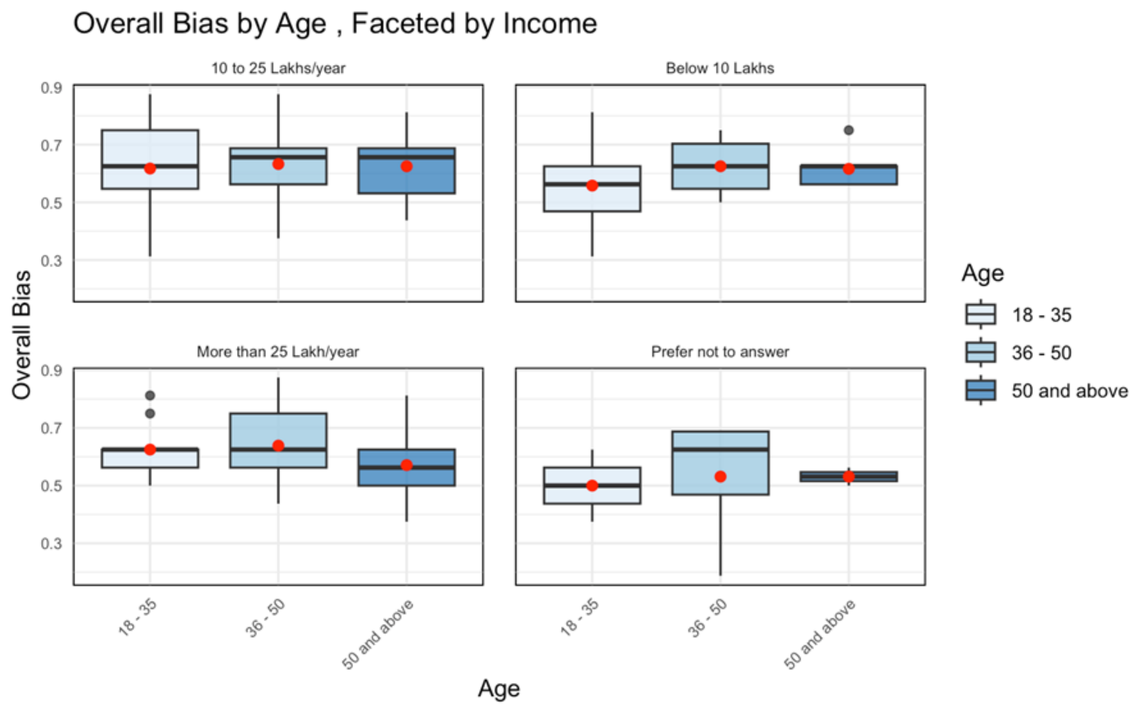

Overall Bias by Trading.Exp , Faceted by Qualification
Graduate and below
Post Graduate or more
0.9
0.7
0.5
0.3
Overall Bias
0 - 3 years
3- 10 years
More than 10 years
Trading.Exp
Trading.Exp
0 - 3 years
3- 10 years
More than 10 years

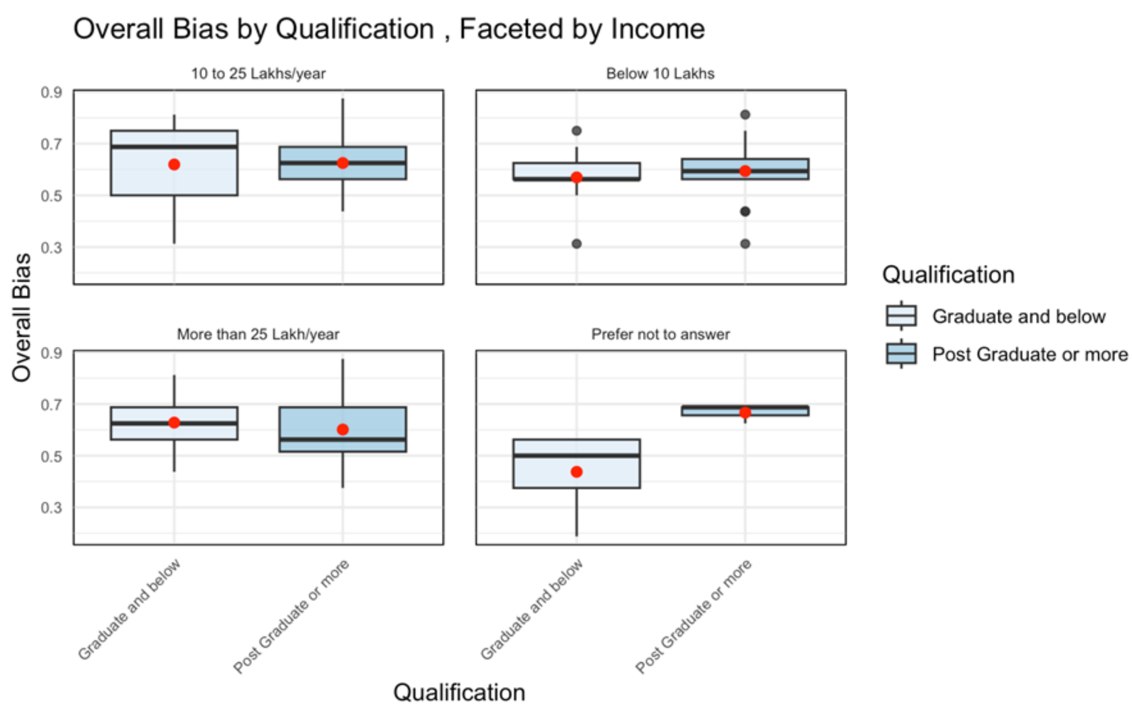

Overall Bias by Gender , Faceted by Occupation
Other
Own Business/ Self employed
Professional
Salaried
Overall Bias
0.9
0.7
0.5
0.3
Female
Male
Gender
Gender
Female
Male


Overall Bias by Qualification , Faceted by Occupation
Other
Own Business/ Self employed
Professional
Salaried
Overall Bias
0.9
0.7
0.5
0.3
Graduate and below
Post Graduate or more
Qualification
Qualification
Graduate and below
Post Graduate or more

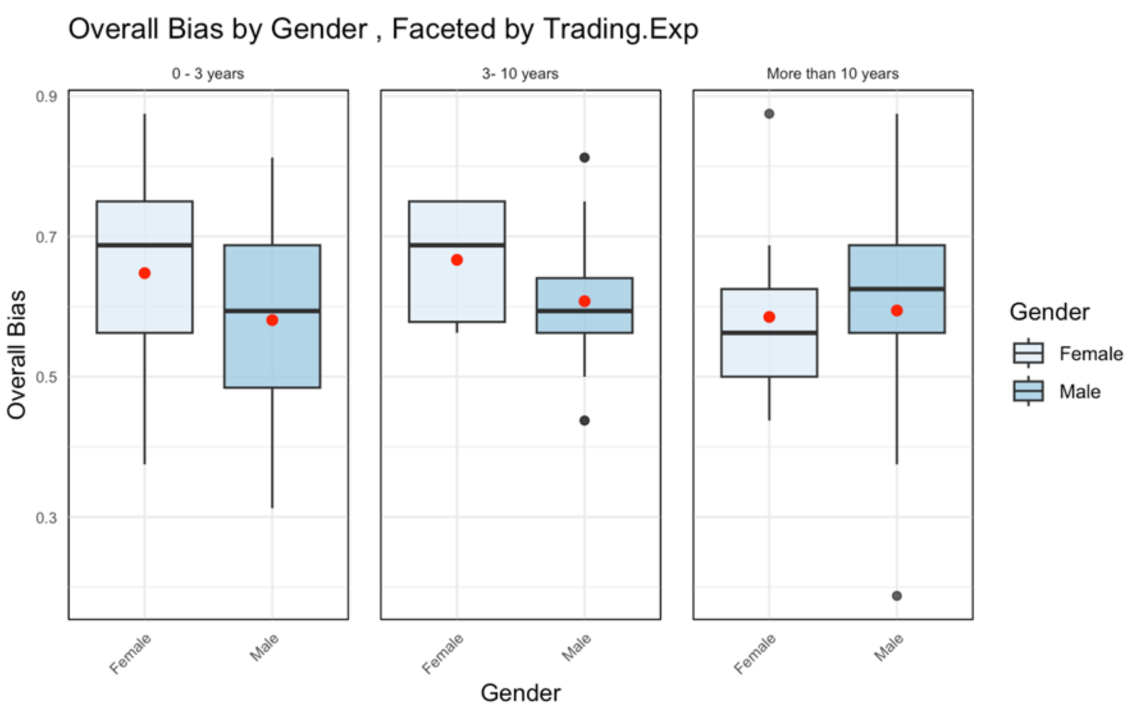

Overall Bias by Trading.Exp , Faceted by Occupation
Other
Own Business/ Self employed
Professional
Salaried
Overall Bias
0.9
0.7
0.5
0.3
0 - 3 years
3- 10 years
More than 10 years
Trading.Exp
Trading.Exp
0 - 3 years
3- 10 years
More than 10 years

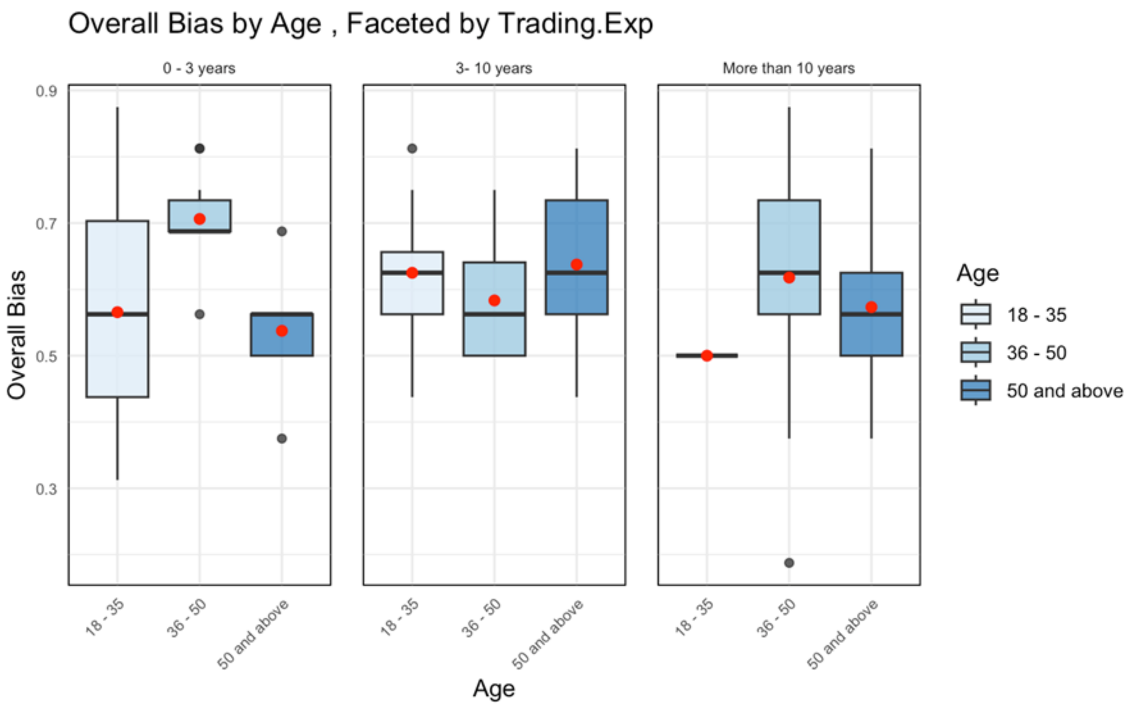

Overall Bias by Gender , Faceted by Income
10 to 25 Lakhs/year
Below 10 Lakhs
More than 25 Lakh/year
Prefer not to answer
Overall Bias
0.9
0.7
0.5
0.3
Female
Male
Gender
Gender
Female
Male


Overall Bias by Age , Faceted by Income
10 to 25 Lakhs/year
Below 10 Lakhs
More than 25 Lakh/year
Prefer not to answer
0.9
0.7
0.5
0.3
Overall Bias
18 - 35
36 - 50
50 and above
Age
Age
18 - 35
36 - 50
50 and above


Overall Bias by Qualification , Faceted by Income
10 to 25 Lakhs/year
Below 10 Lakhs
More than 25 Lakh/year
Prefer not to answer
0.9
0.7
0.5
0.3
Overall Bias
Graduate and below
Post Graduate or more
Qualification
Qualification
Graduate and below
Post Graduate or more


Overall Bias by Trading.Exp , Faceted by Income
10 to 25 Lakhs/year
Below 10 Lakhs
More than 25 Lakh/year
Prefer not to answer
Overall Bias
0.9
0.7
0.5
0.3
0 - 3 years
3- 10 years
More than 10 years
Trading.Exp
Trading.Exp
0 - 3 years
3- 10 years
More than 10 years


Overall Bias by Gender , Faceted by Trading.Exp
0 - 3 years
3- 10 years
More than 10 years
Overall Bias
0.9
0.7
0.5
0.3
Female
Male
Gender
Gender
Female
Male


Overall Bias by Age , Faceted by Trading.Exp
0 - 3 years
3- 10 years
More than 10 years
Overall Bias
0.9
0.7
0.5
0.3
18 - 35
36 - 50
50 and above
Age
Age
18 - 35
36 - 50
50 and above


Overall Bias by Qualification , Faceted by Trading.Exp
0 - 3 years
3- 10 years
More than 10 years
Overall Bias
0.9
0.7
0.5
0.3
Graduate and below
Post Graduate or more
Qualification
Qualification
Graduate and below
Post Graduate or more

Source: Created by the author

AVONA Test Results on Investors

Respondents	Count	Sum	Average	Variance
1	16	10	0.625	0.25
2	16	7	0.4375	0.2625
3	16	10	0.625	0.25
4	16	13	0.8125	0.1625
5	16	10	0.625	0.25
6	16	8	0.5	0.266667
7	16	9	0.5625	0.2625
8	16	9	0.5625	0.2625
9	16	12	0.75	0.2
10	16	9	0.5625	0.2625
11	16	9	0.5625	0.2625
12	16	7	0.4375	0.2625
13	16	9	0.5625	0.2625
14	16	9	0.5625	0.2625
15	16	11	0.6875	0.229167
16	16	7	0.4375	0.2625
17	16	10	0.625	0.25
18	16	8	0.5	0.266667
19	16	14	0.875	0.116667
20	16	9	0.5625	0.2625

21	16	7	0.4375	0.2625
22	16	10	0.625	0.25
23	16	9	0.5625	0.2625
24	16	11	0.6875	0.229167
25	16	9	0.5625	0.2625
26	16	11	0.6875	0.229167
27	16	8	0.5	0.266667
28	16	13	0.8125	0.1625
29	16	9	0.5625	0.2625
30	16	11	0.6875	0.229167
31	16	7	0.4375	0.2625
32	16	8	0.5	0.266667
33	16	6	0.375	0.25
34	16	10	0.625	0.25
35	16	10	0.625	0.25
36	16	11	0.6875	0.229167
37	16	7	0.4375	0.2625
38	16	6	0.375	0.25
39	16	8	0.5	0.266667
40	16	8	0.5	0.266667
41	16	10	0.625	0.25
42	16	10	0.625	0.25
43	16	7	0.4375	0.2625

44	16	10	0.625	0.25
45	16	13	0.8125	0.1625
46	16	11	0.6875	0.229167
47	16	6	0.375	0.25
48	16	9	0.5625	0.2625
49	16	10	0.625	0.25
50	16	12	0.75	0.2
51	16	9	0.5625	0.2625
52	16	7	0.4375	0.2625
53	16	9	0.5625	0.2625
54	16	9	0.5625	0.2625
55	16	11	0.6875	0.229167
56	16	12	0.75	0.2
57	16	9	0.5625	0.2625
58	16	11	0.6875	0.229167
59	16	11	0.6875	0.229167
60	16	9	0.5625	0.2625
61	16	10	0.625	0.25
62	16	12	0.75	0.2
63	16	8	0.5	0.266667
64	16	11	0.6875	0.229167
65	16	7	0.4375	0.2625
66	16	5	0.3125	0.229167

67	16	13	0.8125	0.1625
68	16	8	0.5	0.266667
69	16	7	0.4375	0.2625
70	16	7	0.4375	0.2625
71	16	12	0.75	0.2
72	16	11	0.6875	0.229167
73	16	7	0.4375	0.2625
74	16	12	0.75	0.2
75	16	9	0.5625	0.2625
76	16	12	0.75	0.2
77	16	10	0.625	0.25
78	16	8	0.5	0.266667
79	16	9	0.5625	0.2625
80	16	3	0.1875	0.1625
81	16	9	0.5625	0.2625
82	16	8	0.5	0.266667
83	16	11	0.6875	0.229167
84	16	9	0.5625	0.2625
85	16	11	0.6875	0.229167
86	16	5	0.3125	0.229167
87	16	11	0.6875	0.229167
88	16	12	0.75	0.2
89	16	12	0.75	0.2

90	16	12	0.75	0.2
91	16	11	0.6875	0.229167
92	16	10	0.625	0.25
93	16	11	0.6875	0.229167
94	16	10	0.625	0.25
95	16	9	0.5625	0.2625
96	16	10	0.625	0.25
97	16	9	0.5625	0.2625
98	16	10	0.625	0.25
99	16	7	0.4375	0.2625
100	16	9	0.5625	0.2625
101	16	8	0.5	0.266667
102	16	8	0.5	0.266667
103	16	10	0.625	0.25
104	16	9	0.5625	0.2625
105	16	9	0.5625	0.2625
106	16	9	0.5625	0.2625
107	16	10	0.625	0.25
108	16	12	0.75	0.2
109	16	12	0.75	0.2
110	16	9	0.5625	0.2625
111	16	12	0.75	0.2
112	16	9	0.5625	0.2625

113	16	6	0.375	0.25
114	16	8	0.5	0.266667
115	16	10	0.625	0.25
116	16	10	0.625	0.25
117	16	7	0.4375	0.2625
118	16	10	0.625	0.25
119	16	10	0.625	0.25
120	16	12	0.75	0.2
121	16	12	0.75	0.2
122	16	11	0.6875	0.229167
123	16	12	0.75	0.2
124	16	11	0.6875	0.229167
125	16	14	0.875	0.116667
126	16	12	0.75	0.2
127	16	9	0.5625	0.2625
128	16	14	0.875	0.116667
129	16	11	0.6875	0.229167
130	16	9	0.5625	0.2625
131	16	9	0.5625	0.2625
132	16	6	0.375	0.25
133	16	8	0.5	0.266667
134	16	5	0.3125	0.229167
135	16	10	0.625	0.25

136	16	13	0.8125	0.1625
137	16	10	0.625	0.25
138	16	9	0.5625	0.2625
139	16	13	0.8125	0.1625

ANOVA- 1 Factor	ALFA = 0.05					
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Respondants	36.26439	138	0.262785	1.098975	0.210212	1.214612
Within Respondant	498.5625	2085	0.239119			
Total	534.8269	2223				
Result	The means are NOT SIGNIFICANTly different between Responder					

ANOVA Test Results of Investors' Independent Biases

Biases	**Count**	**Sum**	**Average**	**Variance**
Optimism	139	73	0.52518	0.251173
Gambler Fallacy	139	23	0.165468	0.139089
Recency	139	78	0.561151	0.248045
Bounded Rationality	139	79	0.568345	0.247107
Loss Averse	139	106	0.76259	0.182358
Status Quo	139	86	0.618705	0.237619
Self-Attribution	139	88	0.633094	0.233969
Herding	139	110	0.791367	0.166302
Over-Optimism	139	127	0.913669	0.079449
Representativeness	139	105	0.755396	0.186112
Home Bias	139	130	0.935252	0.060995
Men Accounting	139	39	0.280576	0.203316
Disposition Effect	139	48	0.345324	0.227713
Self-Control	139	78	0.561151	0.248045
Hindsight Bias	139	44	0.316547	0.217913
Over-Confidence	139	115	0.827338	0.143885

ANOVA- 1Factor -Alpha 0.05						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Biases	110.7406	15	7.382704	38.43795	7E-100	1.670915
Within Biases	424.0863	2208	0.192068			
Total	534.8269	2223				
Result	The means are SIGNIFICANTly different between Biases					

APPENDIX F

VARIANCE–COVARIANCE MATRIX OF BIASES

	Optimism	Gambler Fallacy	Recency	Bounded Rationality	Loss Averse	Status Quo	Self Attrb	Herd	Over Optimism	Representativeness	Home Bias	Mental Account	Disposition Effect	Self-Conrol	Hindsight Bias	OverConfidence
Optimism	0.249366	0.027682	0.016147636	-0.01346	-0.00615	-0.00192	-0.00846	0.012687	0.005767	-0.00923	0.011918	0.01115	0.006536	0.039216	-0.00577	-0.00077
Gambler Fallacy	0.0276817	0.138088	0.022128241	0.00141	-0.0123	-0.00748	-0.00094	0.002862	-0.00517	-0.01773	0.012218	0.009953	0.002179	0.010167	0.013157	0.020249
Recency	0.0161476	0.022128	0.246260546	0.000641	-0.01807	0.030074	0.010466	0.019522	0.008544	-0.02093	0.014268	0.014823	-0.01743	0.001452	0.029946	0.012175
Bounded Rationality	-0.013456	0.00141	0.000640779	0.245329	-0.01653	0.01948	-0.0132	0.007818	0.022171	0.019864	0.008202	0.01948	-0.01961	-0.00218	-0.01128	0.019992
Loss Averse	-0.006151	-0.0123	-0.01806997	-0.01653	0.181047	0.002307	0.021915	0.009612	0.006151	0.028066	0.009227	0.008843	-0.01307	0.019608	0.000384	-0.00692
Status Quo	-0.001922	-0.00748	0.030073903	0.01948	0.002307	0.235909	0.013157	-0.00085	0.007006	0.012901	0.018497	-0.00209	-0.01089	-0.01816	0.00534	-0.02858
Self Attrb	-0.008458	-0.00094	0.01046606	-0.0132	0.021915	0.013157	0.232286	0.025289	-0.00607	0.006365	0.005425	0.010979	-0.0305	0.001452	0.018412	-0.00243
Herd	0.0126874	0.002862	0.019522406	0.007818	0.009612	-0.00085	0.025289	0.165105	0.001837	0.008245	-0.0085	0.014396	-0.00871	0.011619	0.018497	-0.00179
Over Optimism	0.005767	-0.00517	0.008543722	0.022171	0.006151	0.007006	-0.00607	0.001837	0.078878	0.03174	0.013499	-0.00171	0.002179	-0.00508	-0.01311	0.022555
Representativeness	-0.009227	-0.01773	-0.02093212	0.019864	0.028066	0.012901	0.006365	0.008245	0.03174	0.184773	0.002221	0.036866	-0.01089	0.016703	-0.0499	0.00487
Home Bias	0.0119185	0.012218	0.014268017	0.008202	0.009227	0.018497	0.005425	-0.0085	0.013499	0.002221	0.060556	0.007604	-0.00218	0.013798	0.009014	0.012047
Mental Account	0.0111496	0.009953	0.014823359	0.01948	0.008843	-0.00209	0.010979	0.014396	-0.00171	0.036866	0.007604	0.201853	-0.02397	0.042847	0.003161	0.004101
Disposition Effect	0.0065359	0.002179	-0.01742919	-0.01961	-0.01307	-0.01089	-0.0305	-0.00871	0.002179	-0.01089	-0.00218	-0.02397	0.226075	0.017429	0.041394	-0.00654
SelfConrol	0.0392157	0.010167	0.001452433	-0.00218	0.019608	-0.01816	0.001452	0.011619	-0.00508	0.016703	0.013798	0.042847	0.017429	0.246261	0.00581	-0.00871
Hindsight Bias	-0.005767	0.013157	0.029945747	-0.01128	0.000384	0.00534	0.018412	0.018497	-0.01311	-0.0499	0.009014	0.003161	0.041394	0.00581	0.216345	-0.03127
OverConfidence	-0.000769	0.020249	0.012174805	0.019992	-0.00692	-0.02858	-0.00243	-0.00179	0.022555	0.00487	0.012047	0.004101	-0.00654	-0.00871	-0.03127	0.14285

Portfolio Variance Calculation of Biases

Biases	**Weightage**	**Variance**
C_Optimism	0.05	0.25
C_Gambler Fallacy	0.02	0.14
C_Recency	0.06	0.25
C_Bounded Rationality	0.06	0.25
E_Loss Averse	0.08	0.18
E_Status Quo	0.06	0.24
E_Self Attrb.	0.07	0.23
E_Herd	0.08	0.17
C_Over Optimism	0.1	0.08
C_Representativeness	0.08	0.18
C_Home Bias	0.1	0.06
C_Mental Acc.	0.03	0.20
E_Disposition Effect	0.04	0.23
E_Self Conrol	0.06	0.25
E_Hindsight Bias	0.03	0.22
E_Over Confidence	0.09	0.14

Mean of Variance of biases (w/o corvariance effects bewteen biases)	Sum of Variances ÷ 16	0.19
Portfolio Variance (Net-Bias) of biases (with covariance effects between biases)	Formula using “MMULT” function in MS EXCEL	0.0168

APPENDIX F

LIST OF ABBREVIATIONS

1. AMH – Adaptive Market Hypothesis
2. BAPM – Behavioural Asset Pricing Model
3. BF – Behavioural Finance
4. BPT- Behavioural Portfolio Theory
5. CAPM – Capital Asset Pricing Model
6. EMH – Efficient Market Hypothesis
7. GE – General Elections
8. MPT- Modern Portfolio Theory
9. TRA – Theory of Reasoned Actions