INVESTOR PSYCHOLOGICAL BIASES AND VOLATILITY OF SHARE PRICE IN NAIROBI SECURITIES EXCHANGE, KENYA

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DECLARATION

This research project is my original work and has not been presented elsewhere for a degree or any other award.

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DEDICATION

I dedicate this work to my mother, Rosemary Karugano, my father Jeremiah Karugano, my husband, Kelvin Kariuki and to my brothers,Sammy Nyaga, Mark Kariuki ,Edwin Chomba and my sister Georgian Wawira for the endless support, love and encouragement throughout this entire journey.

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ACRONYMS AND ABBREVIATIONS

CMA:	Capital Markets Authority
EMH:	Efficient Market Hypothesis
FISE:	Fixed Income Securities
GARCH:	Generalized Autoregressive Conditional Heteroscedasticity
IPO:	Initial Public Offer
NSE:	Nairobi Securities Exchange
OLS:	Ordinary Least Squares
SDGs:	Sustainable Development Goals
USD:	United State Dollar

DEFINITION OF TERMS

Loss aversion: Investor propensity to give more weight to losses than they do to gains.

Mental accounting: Investors' method of coding and evaluating financial outcomes, investments, transactions, and gambles.

Overconfidence: Tendency of an investor to attribute success to own abilities and precision of information, while blaming "bad luck" for the failures.

Psychological bias: Human tendency that lead investors to follow a particular mental notion and beliefs.

Share price volatility: The rate at which share price increases or decreases over a period.

ABSTRACT

The importance of financial markets in an economy cannot be understated. The markets contribute to economic growth through resource allocation and liquidity creation for businesses. The merits are perfectly achieved if the markets are efficient and information about the market reaches the market participants in a timely and accurate manner. Kenya's securities market has experienced high share price volatility in the recent past, leading to unfavorable outcome to investors. While the investors in the financial market expect to reap optimal returns, this has not been the case due to their decisions, which are inconsistent, irrational and misjudged. Investor's psychological biasness is the contributing factor to the irrational decisions by investors in financial market. This study therefore aimed at investigating the effect of psychological biases on the volatility of the share price among the listed companies on the Nairobi Securities Exchange. The study aim at controlling share price unpredictability among the listed stocks. The study employed efficient market hypothesis, prospect and irrational theories, and behavioral finance theory in examining the psychological biases and share price unpredictability nexus. A causal research design was employed on 59 corporations registered in the NSE between 2014 and 2023. Panel GARCH model was adopted by the current study as the estimation model to appropriately capture the share price volatility. Based on the hypothesis that investor psychological biases (overconfidence, loss aversion, and mental accounting) influence share price volatility, this study revealed the following; First, that there exists a negative and significant relationship between overconfidence and volatility of share price. Secondly, the study revealed that loss aversion had a negative significant effect on the share price volatility across the manufacturing and processing, commercial Services, and pooled (sum of the two categories). Third, that mental accounting has a positive and significant effect on the share price volatility across the manufacturing and processing, commercial services, and pooled NSE-listed companies. The study findings provide policymakers with the needed information on the role psychological biases on managing share price volatility. The findings also enhance investors' knowledge on psychological biases, help them to respond appropriately to avoid such biases while making investment decisions. Lastly from an empirical perspective, the outcome of this study contribute to literature and existing knowledge by revealing the relationship between investor psychological biases and the share price volatility.

CHAPTER ONE
INTRODUCTION

1.1 Background of the Study

Financial marketplaces contribute to a critical role in financial growth through allocation of resources and liquidity creation for businesses and individual entrepreneurs (Hu & Wang, 2022). Research has shown that a country's local financial markets activities enhances economic stability fundamentally by refining access to capital and resident companies cost of capital (Barajas et al., 2020). The key functions of the financial market in regards to resident firms' operational considerations include efficient transfer and allocation of financial resources, risk sharing and provision of information to market participants (Hu & Wang, 2022). An annual investment of about 4.0 trillion US dollars is required for mounting countries capability to achieve the Sustainable Development Goals (SDGs) (World Bank, 2019). To achieve the market roles and a country's investment goals, the financial markets must remain efficient, well-functioning and efficiently supervised.

Financial markets display certain behaviors that may not be fully explained by traditional economic concepts. Even though the empirical evidence in the past recent years have shown that markets are highly efficient, there exist several studies which have found trends of inconsistency, irrationality, and misjudgments when investors make decisions in uncertain environments (Bertella et al., 2020). In the recent years, financial market volatility has attracted the attention of investors who are ever apprehensive about their investment returns and risks associated to them. Information flow influences investors' decisions about the market, in which price share unpredictability is highly related to (Chaoudhary, 2022).

The natural fluctuation designs of the day-to-day prices share are suggestive of the stochastic picture of the economic marketplaces. Investors often take the risk of investing their resources in the stocks expecting to make more returns in the future regardless of these movement in prices, (Parveen et al., 2020). Stakeholders in standard marketplace remain absorbed in the unpredictability of prices share as great unpredictability might indicate vast risk losses or earnings at the expense of better ambiguity (Özelli, 2020). Literature has pointed out that unpredictability is better however can simply be detrimental if the price share fluctuations are so great and quick over precise times because it hampers monetary arrangement (Babaei, 2024). Implicitly, great variations in price of shares can upsurge equally risk and ambiguity about the returns in future. Since forecast of stock is a portion of stock interchange, the unstable marketplace enactment leaves financiers unexperienced of what the forthcoming holds for them in terms of future price changes. Consequently, investors would shy away from making investments. A volatile market impedes listed firms to increase resources in the wealth marketplaces. Investor's confidence, which is important in stock trading and leverage decision, is lost when there is uncertainty. Thus, understanding market volatility is of great significance in allowing financiers to cope risks then maximize returns.

To enhance returns from investment, investors must make rational decisions and not predict stock performance based on prices of shares only (Parveen et al., 2020). Psychologists have however shown that human beings do not exhibit rational behavior as economists would expect (Cushman, 2020). The stock market anomalies experience so far, and studies conducted by Akhtar and Das (2020) and Bertella et al., (2020) discovered that financiers do not always make lucid decisions as always expected they would be. Market anomalies are explainable by behavioral finance, an emerging area in finance. Behavioral finance describes the effect of individual or group's psychological traits on their investment, analysis and portfolio management behaviors (Akhtar & Das, 2020). Behavioral finance explains how cognitive errors and emotions influence individual investor's behavior (Jain et al., 2020). Proponents of behavioral finance have put forward a quantity of mental factors that influence investors' making their decisions in the financial marketplace. The study investigates how psychological biases, particularly the overconfidence bias, loss aversion unfairness and availability unfairness could affect decisions on investment, hence market volatility.

The Nairobi Securities Exchange (NSE) has witnessed high volatility of share price in the past (Cherono et al., 2019), an indication of possible inefficiencies in the market which affects shareholder value. Some of these inefficiencies in the NSE could be attributed to investors' behaviors on the basis of mental notions and beliefs. For example, in 2008 Safaricom IPO was tremendously oversubscribed traded and ended up trading at below Kshs. 5.00 for more than five years after the IPO, with the stock going for as low as Kshs. 2.00. The oversubscription for this stock was an overreaction behavior witnessed among investors. This was caused by the abnormal and high returns from the 2006 KenGen IPO, whose share price tripled after listing the offer at Kshs. 11.90 per share. The oversubscription was a true indication of the effect of psychological bias on individual investor's decision resulting to high price share volatility.

1.1.1 Investor Psychological Biases

Investor behavior at the stock markets including NSE may follow a particular mental notion in relation to important approximations as of irregularities such as herding conduct, overconfidence, loss dislike and mental accounting. Overconfidence is the habit of an individual to base their success to own abilities and precision of information, while blaming "bad luck" for the failures, thus overestimating abilities and underestimating the future uncertainties (Bibi, 2021). If shareholders overestimate their aptitude to produce data or to classify the importance of present information that other investors abandon, they will undervalue their estimate mistakes. They will not incline to be overconfident about public signals but about the data generated. Therefore, the individual who overrates the exactness of their personal data signal instead of established visibly data signals is defined as an overoptimistic investor. Overconfident financiers may be more ready to sell winners because the run-up they expected had occurred. The investors are, however, less willing to sell losers because they are confident that the run-up will eventually take place (Awino, 2021). Such a scenario was witnessed in the shares of Mumias Sugar Company, which was a demonstration of mismanagement effect on shareholder's wealth.

Individual investors may have a higher propensity to sell shares trading at a gain comparative to buying amount, instead of selling stock trading at a loss. This behavior describes loss aversion, where financiers in a standard marketplace provide additional burden to losses than they do to gains. In NSE, loss aversion was seen among investors who held shares of Uchumi Supermarket Limited. The firm started experiencing operational and financial difficulties in early 2000s due to mismanagement, poor internal control systems, and poorly planned expansion strategy (Jacob et al., 2018). As a result, the firm's shares were losing value (Cherono et al., 2019). Investors nonetheless, continued to hold the shares with hope that the company's financial performance will improve. In this case, human psychology influenced investors choices, assessment of returns and investment decisions at the NSE (Mamun & Hasanuzzaman, 2020).

Mental accounting refers to investors' method of coding and evaluating financial outcomes, investments, transactions, and gambles. Intellectual accounting defines individual's propensity to put actions into various intellectual accounts built on artificial qualities. As such, at times people separate decisions which should ordinarily be combined. This psychological behavior explains why investors may refrain from regarding their reference point for a standard stock. A new intellectual account is normally opened when a stock has been purchased. In order to indicate gains or losses comparative to price purchase, a succession notch is kept on this account. Intellectual accounting and seeking risk combination (Xue et al., 2018) in the field of losses Bibi (2021) enable financiers to relax on losing investments and trading winners. In making distinctions that do not financially exist, great number of private investors engage in mental accounting. Frequently, losses earned are regarded distinctly from paper losses. This incurs that too rapidly when investors earn their profit and too late when they incur losses, they normally sell stocks from their portfolio. In addition, making paper profit into real profit makes investors excited but become reluctant in converting a paper loss into real loss.

1.1.2 Share Price Volatility

The inconsistency in the stock returns as a result of daily share changes in price is commonly named as volatility with standard deviation of returns used to measure (Bhowmik & Wang, 2020). Babaei (2024) describe unpredictability as a percentage of variance between a stock existing prices and its average prices from the past. Thus, volatility is the standard deviation of returns, which measures the spreading of returns from the average. Price of shares will change on a daily basis when stock buyers and sellers keenly participate in the marketplace with an aim of getting returns and making value for their investment. If many investors are interested in buying (selling) a stock than selling (buying) it, the prices move up (down). These value movements define the yield and ultimately the unpredictability of the marketplace.

Volatility of share price is characterized by a group of slight and great moves of share prices known as volatility crowding and today's volatility shocks, which impact the anticipation of future's volatility (Chaoudhary, 2022). Parveen et al. (2020) discuss that volatility clustering implies that large variance of returns (changes of prices) are probable to be trailed by additional great variance, the great volatility continues for a shorter period after the original shock. Likewise, small changes in prices are likely to be followed by a period of low volatility. Literature suggest that several factors such as psychological biases, inflation, latest information on share prices, market economic strength, and company's future uncertainty influence price movements Chaoudhary (2022); Cushman (2020); Lalwani, Sharma, & Chakraborty, 2019; Chaoudhary (2022); Parveen et al. (2020). With the existence of price volatility in NSE which results to unfavorable returns to investors, this study intends to specifically examine the psychological biases effect on the share price volatility.

Literature notes that in the case of price share unpredictability there are different behaviors of most market (Ngure et al., 2022;Özelli, 2020). Lalwani et al. (2019) observed that the the swiftness varies from market to market in correcting prices after a shock. For instance, China stock market was found to correct the prices within a few hours after the price shocks while in other markets like Switzerland and India stock markets, correction could last for more than 6 days after an event. Rupande, Muguto, and Muzindutsi (2019) observed that return in the stock unpredictability significantly increases between the yeart 2002 and 2018 in the Johannesburg stock exchange. Compared to other East Africa countries, NSE has greater price share volatility Ngure et al. (2022), hence the need to investigate the contribution of investor psychological biases to the high volatility.

1.1.3 Investor Psychological Biases and Share Price Volatility

According to Parveen et al., 2020, the trading patterns of stocks in the financial market have been linked to the prevailing biased behavior of investor. At a particular level of risk, Distinct financiers invest with a reasonable expectation of returns in the financial market. (Chaoudhary, 2022). In pricing a monetary asset, the trade-off between risk and yield is very critical Chaoudhary (2022), thus the unpredictability of stock yield arise from risk level associated with the stock. Risk and return being related positively, between expected return and unpredictability of returns vitality, there should be a positive relationship and between realized returns and unexpected vitality there should be a negative relationship. The occurrence of final relationship is observed when there is unanticipated rise in vitality which increases return rates required which later decreases stock prices (Chaoudhary, 2022). Irrational traders normally enter the market in times of high psychological biases because greater optimism interpretation in great psychological bias times as ultimate data, instead of seeing it as a signal which is noisy (Jacob et al., 2018).

1.1.4 Nairobi Securities Exchange

Created in 1954, the NSE has been one of the leading securities markets in Africa. The market, which lists both equity and debt securities, is popularly known as a global trading platform for investors seeking revelation to the economic growth of both Kenya’s and Africa’s. The NSE is classified as one of the markets in emerging economies, having 63 listed stocks from 11 sectors (Weru, 2019). Financial markets in emerging economies are often disadvantaged in terms of low trading volume, low turnover ratios, inefficient information dissemination and few listed firms (Jacob et al., 2018). In East Africa, NSE is the strongest stock market compared to other markets in East Africa Community such as Stock Exchange in Rwanda, stock exchange in Rwanda and Tanzania with low number of listed firms and low market capitalization (Ngure et al., 2022). Trading activity has gradually increased over the last three to five years, according to NSE financial reports. Trading volume in the Fixed Income Securities Market (FISE) increased by 42% in 2016 from Kshs. 305 Billion in 2015. Trading volume in the FISE increased by 0.82 percent in 2017 from Kshs. 432 billion in 2016 to Kshs. 435 billion. The Fixed Income Securities Market's secondary trading activity increased by 29% from Kshs. 435 billion in 2017 to Kshs. 562 billion in 2018. A 2018 analysis showed that 13.6 percent and 35.3 percent for one year and three years' volatility, respectively, in the FISE NSE Kenya 15 Index and a 13.7 percent and 35.4 percent for one year and three-year volatility respectively, for the FISE NSE Kenya 25 Index.

1.2 Statement of the Problem

Decisions made by securities market investors play a pivotal part in defining the market movement, and in turn impacts on economy. Efficient market hypothesis suggests that when investors make rational decisions, the financial market will not experience any share price volatility as forces of demand and supply will be in play. Literature has however shown that financial markets are not always efficient and that overconfidence, mental accounting and loss aversion biases have great effect on volatility.

The Kenya's securities market has indeed experienced high price share volatility resulting to undesirable outcome to investors. Equity market investors in NSE lost about Kshs. 500 billion in 2016 to a market value of Kshs. 1.93 trillion from Kshs. 2.42 trillion, when share prices declined by 25.35%. Prior to this, investors in NSE suffered a loss after Safaricom shares traded below the nominal value of Kshs. 5 for more than five years having floated an IPO in 2008 with a market value of Kshs. 2. During the COVID-19 pandemic, foreign investors at NSE sold off shares in the blue-chip firms over the lockdown in 2020, making NSE experience the largest daily drops in its history (NSE, 2020). These undesirable outcomes could be attributed to investor psychological biases which have taken prominence over rational behavior pertaining to stock market investments. Since the loss occurred in the stock market, there has been limited demand for stocks due to the continuous wait-and-see attitude by financiers amid tenacious price unpredictability.

Recent studies on behavioral finance in Kenya have examined investment decision effect of random walk, frame independence, overconfidence, availability bias, herding behavior, fear of regret, and anchoring (Weru, 2019). Little studies have focused on overconfidence, loss aversion and mental accounting as biases among NSE investors and their effect on dramatic share price volatility. This study therefore, attempts to close the gap knowledge by revealing what drives the high price share unpredictability of organizations in the NSE. Specifically, this study aims at examining the overconfidence, loss aversion and mental accounting effect on price share unpredictability for organizations registered in NSE.

1.3 Research Objectives

The study had both broad and specific objectives.

1.3.1 General Objectives

The overall objective of this study was to determine the effect of investor psychological biases on share price volatility among firms listed in the NSE.

1.3.2 Specific Objectives

The study sought to achieve the following objectives:

1. To investigate the effect of overconfidence on share price volatility among firms listed in NSE.
2. To establish the effect of loss aversion on share price volatility among firms listed in NSE.
3. To assess the effect of mental accounting on share price volatility among firms listed in NSE.

1.4 Research Hypotheses

H_{01}: Overconfidence has no effect on share price volatility among firms listed in NSE.

H_{02}: Loss aversion has no effect on share price volatility among firms listed in NSE.

H_{03}: Mental accounting has no effect on share price volatility among firms listed in NSE.

1.5 Scope of the Study

The study was limited to 59 firms listed in NSE from 2014-2023. The study focussed on overconfidence, loss aversion, and mental accounting.

1.6 Significance of the Study

The outcome of this study assists securities market players and investors in being mindful of the influence of their own psychological biases on changes in the price share in the stock market. With this information, the investors enhance their knowledge in understanding the role of psychological factors on price share volatility, and take measures to prevent the biases from interfering with their investment decisions to make rational decisions. Additionally, the study is useful to regulators of the stock market and policymakers in understanding the role psychological biases play in high share price volatility. This research also contributes to financial research relating to behavioral finance and is useful as reference by future researchers. This is because it sheds light on efficient market hypothesis (EMH) which assume perfect rationality behavior of individual investors.

1.7 Study Limitations

The main limitation of the current study is the assumption that the relationship between price share volatility and psychological biases is linear and the direct relationship between these variables was tested. Future studies can be conducted using other estimation models while testing for a symmetric relationship between share price volatility, overconfidence, mental accounting and risk aversion.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This part analyses previous research work on the effect of psychological biases on price share volatility as well as related theories which serve as basis for research development. The conceptual framework, and research gaps are also highlighted in this section.

2.2 Theoretical literature review

Several theories in were reviewed to investigate the effects of investor psychological biases on price share volatility in the Nairobi Securities Exchange market.

2.2.1 Efficient Market Hypothesis

The efficient market hypothesis depicts the work of Fama (1970). According to this theory share prices mirrors the existing data regarding the marketplace system hence an investor is not likely to earn surplus profits from the available information. It describes a system where numerous active, profit maximizing and rational investors strive to make a correct prediction of market value of securities to take advantage of future fluctuations given the available information (Ouma & Oluoch, 2019). However, to availability of full information about the market, it is difficult any investor to outperform the market. The efficient market hypothesis theory further posits that stocks tend to trade at their fair value in most of the times it is unusual for traders to purchase an under or overvalued stock. Furthermore in case the stock is undervalued, it is likely to attract more traders hence rising its demand which translates to increased prices (Mohrschladt & Langer, 2020).

In this regard, the EMH theory is structured in three forms as strong EMH which posits that price of shares in the market is a reflection of information in both public and private sector, semi-strong EMH which provides that the price of shares tend to change as soon as the general public learns about the these prices and lastly weak EMH which assumes the prevailing share prices reflect the financial market information (Ogiemudia & Isibor, 2021). The Market information therefore an important determinant of volatility of the share price stimulated by behaviours of the investors in the market who in most cases tend to invest in popular stocks even if the available information on the public domain is inadequate to give critical judgement (Woo et al., 2020).

2.2.2 Prospect Theory

This theory is featured in the work Kahneman and Tversky (1979), who described the behaviour of investors in risk-involving situations. It theorizes that individual investors make investment choices grounded on perceived gains rather than perceived losses. This is because they value gains and losses differently. For investors, losses create high emotive impact than the same level of gains Woo et al. (2020), thus are more affected by losses than they are by gains. The theory contend that investors strive and put more effort to avoid losses, but put less effort to make gains, and will therefore continue holding on losing stocks hoping for the price to increase in future. As such, share prices will change in the market based on the level of gains or losses the investor anticipates from the stock (Babaei, 2024). The theory further explains investors' inability to avoid sunk costs thus tend to take actions which are not in their best interest. While most investors are risk averse, they become risk lovers when trying to avoid the losses (Ngure et al., 2022). The theorists argue that, under uncertain conditions, decisions by investors change from those earlier predicted by standard finance theory, and because of less cognitive capacity, they are unable to analyze data optimally, hence their conscious mind becomes irrational. The theory plays a role in explaining why investors make investment decisions which may be seen to be irrational and how they develop utility from both investment achievements and in the value of their financial wealth (Cherono et al., 2019).

2.2.3 Behavioural Finance Theory

This theory focuses on psychology and seeks to explain how cognitive errors and emotions influence behaviour of individual investors (Cushman, 2020). A lot of research work that have been done in behavioral finance touches on cognitive psychology which is the study of how human beings, including investors reason and make decisions. Behavioral finance posits that investors' choices are influenced by beliefs and preferences which make them to overreact to certain kinds of market information or underreact to others (Akhtar & Das, 2020). The overreaction or under reaction by investors affect their decision making process in relation to the kind of investment they make. The theory works well in a complex environment full of uncertainty by employing common sense in solving a problem. It also eases decision making process by defining a set of evaluation criteria which investors can use in selecting the types of investments to venture into, as well as when to buy or sell the stock (Lalwani et al., 2019).

Previous studies have listed overconfidence and loss aversion biases into the behavioral finance theory (Cushman 2020; Bertella et al., 2020;). This study uses behavioral theory in examining the overconfidence and loss aversion biases effect of volatility on price of shares among the listed stock in NSE.

2.2.4 Irrationality theory

According to this theory, investors often make biased decisions based on their emotions rather than a rational analysis which leads to fluctuation in share prices hence contribution to volatility in the stock market (*Summers,1986.*). The theory suggest that irrational behaviour by investors can lead to higher fluctuations in the share prices than the actual fluctuation which is expected when investors behaviour is purely based on company data analysis. Higher share price volatility than can be explained by a rational economic model is assumed to exist mainly attributed to irrational behaviours such as herd mentality or following the crowd, anchoring biases, overconfidence biases and overweighing recent information biases (Haritha & Rishad, 2020).

Irrational theory also provides that volatility of share prices can be as a result of fear of missing out which happens when traders run to buy a rising stock to take advantage of the projected gains hence further pushing the price of stock up. On the other hand, any bad news relating to a given company can maker traders to rush into selling the stock associated with company hence significantly reducing the price. According Schädler (2018) while irrational theory questions the efficiency of the efficient market hypothesis, some scholars have also argued that irrational behaviours might not always dominate the market dynamics. And even if it happens the market forces tend to correct the irrational behaviours hence containing price fluctuations as investors tend to re-evaluate the company fundamentals before making further sales or purchase decisions.

2.3 Empirical Review

This section discusses previous empirical research conducted on the influence of overconfidence, loss aversion and mental accounting on volatility of share prices.

2.3.1 Overconfidence and Share Price Volatility

A study by Yang et al. (2021) employed covariance based equation model to test the underlying psychological mechanisms on the effect of Malaysian investors' perceived portfolio on their trading and risk taking. The findings revealed that excessive past extrapolation of portfolio made investors to exhibit overconfidence, optimism and risky attitude. These in turn results into risky shareholding, portfolio turnover, and willingness to do more trading, volatility of share prices. This supported by Jain et al. (2020) who found that overconfidence bias significantly influence individual. Silwal and Bajracharya (2021) investigated investor behavior patterns in Ho Chi Minh security market in Vietnam. Data collected from 188 investors were analyzed using factor analysis method. The study findings revealed that anchoring, overconfidence, herding and regret aversion had significant effect on investors' decision making which impacted on prices of shares in the stock market.

In Egypt, Metawa (2018) assessed the impact of overconfidence biases on the investors' financial decisions. The study used structured questionnaires to collect data from local, foreign, institutional and individual investors. A multiple regression model was employed for analysis which revealed no significant nexus between overconfidence and the stock investment decisions. Thus, prices of shares would experience volatility as investors would be biased in their investment decisions. The present study uses historical data examined using panel GARCH regression model.

A study in Kenya by Weru (2019) investigated the overconfidence bias effect on investment decisions by investors at NSE. The research used structured questionnaires to obtain data from 109 investors. Spearman correlation and linear regression analyses were employed in the study. The findings showed that overconfidence had no effect on investment decisions by individual investors. Another study on investor behavioral bias effect on share performance was conducted by Elhussein and Abdelgadir (2020). The study adopted multiple regression in analyzing the primary data collected from 203 individual stock investors. The results revealed that overconfidence significantly and negatively impacted on share performance in stock market in Sudan. The results showed that investors were assuming a lot of risk which let to poor share returns. This study is different from the previous studies as it employ census design and uses secondary financial data from NSE in establishing the effect of psychological biases on the fluctuation of NSE price share.

2.3.2 Loss Aversion and Share Price Volatility

A conceptual framework of the stock market volatility is provided by Chaoudhary (2022) with a review of numerous empirical literature. The study found that investors induce prices of shares variations in the financial market through interpreting the flow of information differently and irrationally. This study point out that share price volatility also arises from psychological issues including loss aversion bias, where the investor reacts irrationally to market information.

A study in Brazil by Bertella et al. (2020) researched on loss aversion and overconfidence nexus on trading volume in artificial stock exchange found out that loss aversion significantly reduced trading volume. This findings indicated that share prices were affected by investors low trading capacity. Similarly, Jain et al. (2020) examined the influence of loss aversion on investment decisions of individual investors in Punjab, India. The study applied Fuzzy analytic hierarchy method to rank the factors that influenced investors' decision making. The researchers found that loss aversion was among the most influential factors that determined decision of individual equity investors, leading to changes in prices of shares in the securities market.

In Rwanda, Ngure et al. (2022) studied the power of behavioral biases in the Rwanda stock exchange investment. Loss aversion bias was considered as the predictor variable while trading volume was the dependent variable. The study used a sample of 374 investors in the stock market. The findings of a linear regression indicated that loss aversion exhibited a positive effect on investment at Rwanda stock exchange. The results further showed that majority of the sampled investors experienced a problem of loss aversion bias in making investment decisions in the stock market. This in turn, affected prices of shares.

In Kenya, Sharon (2022)conducted a study on cognitive biases influence on investors' decisions in NSE. The researcher considered anchoring, random walk, excessive optimism, accounting information and representativeness biases as the independent variables. Data was collected among 69 investors who were participants in NSE market. Data analysis was done using mean scores, frequencies, percentages and multiple regression. The findings indicated that investors' decisions were significantly predicted by the cognitive biases. Cherono et al. (2019) conversely found a significant influence of loss aversion on investors' decision making in NSE. Unlike the previous research, this study focuses on loss aversion as a component of psychological biases, and its effect on share price volatility in NSE. Additionally, the research uses secondary financial data to measure loss aversion and share price volatility.

2.3.2 Mental Accounting and Share Price Volatility

In Spain, Pérez-Espés et al. (2023) conducted a study on the relationship between mental accounting and investment portfolio design based on psychological and financial angles. The researchers found that each investor had own perceptual accounts of risk and return, which they would compare to meet their investment expectations. The results further showed that even though investors had the same investment portfolio and investment environment, and because their risk preferences changed, their investment decision making and expected return was different.

Similarly, Jain et al. (2020) studied how mental accounting bias impacts the investment decisions in Indian stock market. This study employed the Fuzzy analytic hierarchy procedure, the study found that mental accounting bias was a significant determinant of investment decision. According to this study, investors made irrational decisions while making decisions on investments to venture into.

In Kenya, Ouma & Oluoch (2019) evaluated the behavioral biases effect on performance of shares in NSE for a period of one year. The behavioral biases considered in the study included herding behavior, mental accounting and overconfidence, measured as return dispersion, trade volume, and price-dividend ratio respectively. Share performance was measured using share returns based on the price. The descriptive analysis found that mental accounting was a significant contributing factor to share performance in NSE. The present study considered 10-year panel data for analysis. In addition, the study used regression analysis to investigate the effect of psychological effect on volatility of the share price.

2.4 Conceptual Framework

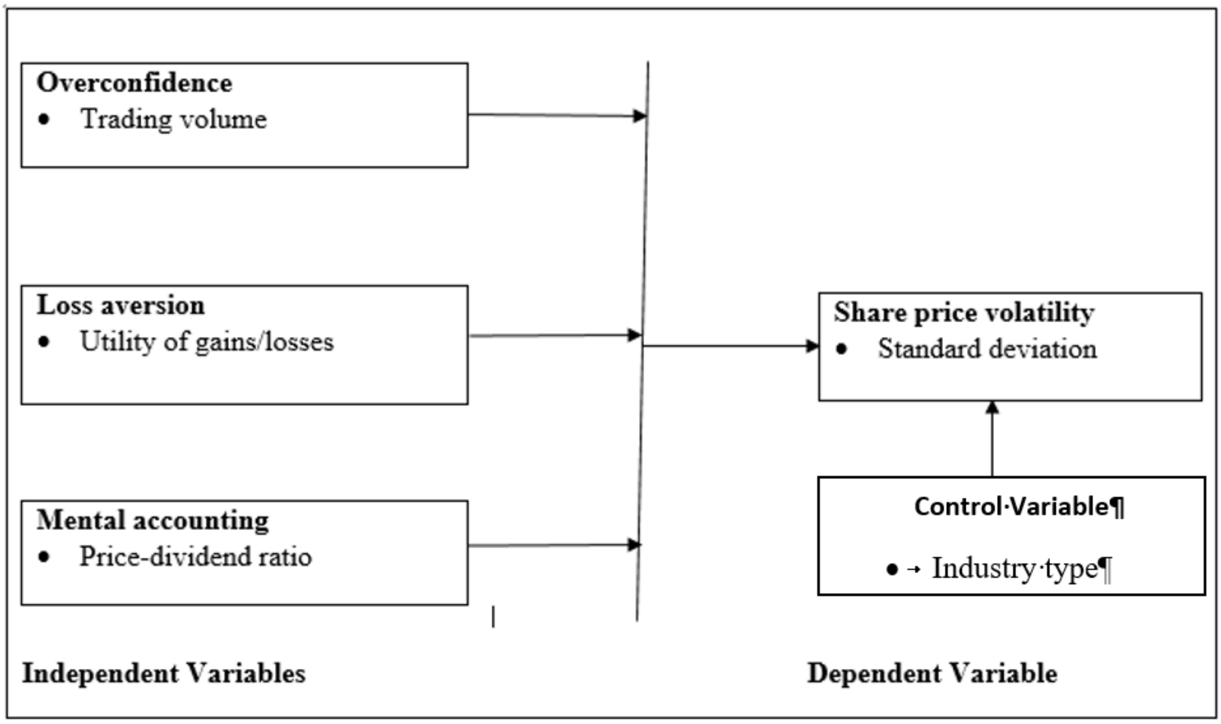

Figure 2. 1: Conceptual Framework

The conceptual framework describes the link between investors' psychological biases and volatility of the share pric (Figure 2.1). The dependent variable is the share price volatility measured by standard deviation while the independent variables include overconfidence bias measured by trading volume, loss aversion measured by utility of gains or losses, and mental accounting measured by price-dividend ratio.

2.5 Summary of Empirical Review

From the studies carried out previously, it is evident that little empirical work has been done on psychological biases, specifically, overconfidence, loss aversion and mental accounting in the Nairobi Securities Exchange. The literature on investors' psychological biases effect on volatility of the share price remains scanty in Kenya and Africa in general (see Cherono et al., 2019; Jacob et al., 2018;; Elhussein and Abdelgadir 2020; Ouma & Oluoch, 2019; Weru, 2019). Most studies have been conducted in mature economies such as Europe, Asia and America, where financial markets are stronger and investors are more knowledgeable in financial markets operations. Furthermore, many of literature on behavioral finance is dependent on data which is generally limited to sub-samples of investor clusters in these states. In Kenya, the few studies that have been conducted focused on herding behavior, random walk, availability bias and representativeness. In addition, the few studies analyzed individual investors' decision making rather than volatility of the share price. Therefore, there is urgent need to understand the share price volatility under aspects of overconfidence, loss aversion, and mental accounting biases.

2.6 Research Gaps

Past studies on the link between investor psychological bias and share price volatility have presented research gaps emanating from both methodology and analysis. The research gaps identified in the previous literature are summarized in Appendix III.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction

This section presents the research design of the study, empirical models and measurement of variable used in the analysis. Data collection instruments and procedures, as well diagnostic are also discussed.

3.2 Research design

A causal research design was employed by the current study covering a panel data spanning 2014 - 2023 for 59 companies listed in the NSE during the study period. The causal research design research was selected for this study.

3.3 Target population

A total of 63 listed firms in NSE formed the study population. However, since the study covers between 2014 and 2023, firms listed in NSE after 2014 were excluded hence only 59 firms were considered for the study. Thus, the research was a census study. The list of the companies listed in NSE is provided in Appendix II

3.4 Data Collection Instruments

Secondary data sourced from financial reports of the NSE over for the period 2014-2023 collected for analysis. Data collection sheet specified in Appendix III was used to record the data.

3.5 Data Collection Procedures

Secondary data was used. This involved a 10-year historical quantitative data on prices of shares, returns, number of exchanges, volume traded, and price dividend ratio of the listed companies. Data schedules shown in Appendix I and conceptual framework in Chapter two guided the data collection process. The NSE historical for 59 out of 63 listed companies covering 2014 to 2023 was collected for analysis.

3.6 Operationalization and variable measurements

Price share volatility was the study's dependent variable, measured as the standard deviation, the amount the share price has differed from the mean annual share price. On the other hand, mental accounting, overconfidence bias and loss aversion were used as independent variables describing the psychological biases.

Volatility of the share price was measured as the standard deviation of share price. This measure indicates how widely share prices are dispersed from the average annual share price as suitable for predicting volatility. The standard deviation was measured as follows:

$$\delta_{i,t} = P_{i,t} - P_{m,t} \quad \ldots\ldots\ldots\ldots \ (3.1)$$

Where $P_{i,t}$ is the actual price observed for all the 59 listed stocks each year, $P_{m,t}$ is the mean annual share price, *t* is the year, and *i* is 59.

Overconfidence was measured by trading volume, computed by turnover as:

$$\text{Turnover} = \frac{n_{it}}{N_{it}} \ldots\ldots\ldots\ldots (3.2)$$

Where n_{it} denotes units of shares of stock *i*, traded per year, N_{it} is the number of exchanges of share *i* (number of deals per year), *t* is the year, and *i* is the listed firm.

On the other hand, loss aversion was measured as annual loss or gain based on previous returns. The gain was calculated as the value of the stock at *i* at time *t+1* less its value at time t multiplied by the risk free-rate. This is presented as follows:

$$X_{i,t+1} = S_{i,t} R_{i,t+1} - S_{i,t} R_{f,,t} \quad \ldots\ldots\ldots\ldots \ (3.3)$$

In which, $X_{i,t+1}$ denotes the gain/ loss in value of stock *i* measured between time t and time *t-/+1* (a positive value implies a gain while negative is loss), $S_{i,t}$ is the reference state of the value of stock *i* at time *t*, $R_{i,t+1}$ is the future expected future return (one year lead), $R_{f,,t}$ is the risk free rate (treasury bill rate).

Price-dividend ratio was used to measure mental accounting. This measure shows how much a firm pays out dividends every year in relation to its share price. This was estimated as as follows:

$$K = \frac{P_0}{D_0} \ldots\ldots\ldots\ldots \ (3.4)$$

Where *K* is the price-dividend ratio, P_0 is the share price at the start of the year while D_0 is dividend paid in the year.

Table 3.1: Operationalization and Measurement of Variables

Dependent variable	Indicator	Measurement	Empirical review

Share price volatility (SPV)	Standard deviation	$\delta_{i,t} = P_{i,t} - P_{m,t}$	Ngure et al. (2022)
Independent variables	**Indicator**	**Measurement**	**Empirical review**
Overconfidence bias (OC)	Trading volume	Turnover = $\frac{n_{it}}{N_{it}}$	Loke (2023)
Loss aversion (LA)	Utility of gains or losses	$X_{i,t+1} = S_{i,\ t} R_{i,\ t+1} - S_{i,t} R_{f,,t}$	Bertella et al. (2020)
Mental accounting (MA)	Price-dividend ratio	$K = \frac{P_0}{D_0}$	Pérez-Espés et al. (2023)
Control variable	**Indicator**	**Measurement**	**Empirical review**
Industry	Dummy	1 if a financial institution and 0 if otherwise	Loke (2023)

3.7 Data Analysis

This study employed panel GARCH model to analyse the relationship between share price volatility and psychological biases. The collected data was classified into three groups as manufacturing and processing firm, commercial services firms and the pooled group, which comprised of the two types of firm. In all estimated models, share price volatility was the dependent variable while psychological biases measures (overconfidence bias, mental accounting and loss aversion) were the explanatory variables. The data analysis was conducted using R statistical software.

3.8 Analytical Model

This study employed a dynamic autoregressive panel model which uses given mean, variance – covariance to specific data. The dynamic model is assumed to follow a GARCH (1,1) process used by (Bhowmik & Wang, 2020). The family of GARCH model is increasingly becoming an important tool for empirical analysis involving financial risk and asset pricing analysis while forecasting and giving volatility estimation. Among recent empirical papers that have employed the model include; (Olamide et al., 2022;Bhowmik & Wang, 2020;Bouras et al., 2019;Deniz et al., 2021). This papers have been motivated by successes of GARCH models in assessing the assets returns and the failure by other deterministic models in predicting price volatility. This is backed by Lin, (2019) who characterized the transition between the risk neutrality and physical probability distribution when dynamic of primitive security is given by the GARCH process. The theoretical knowledge of hedging is also based in GARCH model explained by Wang, (2022) who extended the model characteristics to incorporate jumps in the model meaning that the model can be used in unbalanced panel data.

Specifically, panel GARCH (1,1) model is used by the current study since it is able to capture volatility clustering effect (time periods in which high(low) variations are constantly followed by low(high) variations in financial data), a scenario which stock investors are often keen to look at to avoid loses. Moreover, GARCH (1,1), is able to estimate both the mean and the variance simultaneously a statistical power which lacks in the classical OLS estimator. The study considered a panel dynamic conditional mean equation with investors 's psychological biases (overconfidence, loss aversion and mental accounting) to measure volatility of the share price among NSE listed companies as follows;

$$SP_{i,t}=\rho_i+\sum_{k=1}^{p} \omega_k \, SP_{i,t-k}+\ell_1 IPB_{i,t}+\mu_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.5)$$

Where ρ_i signifies the intercept term of the panel regression, ω_k , (k=1, …, p) represents the coefficients of the AR(P) terms, $\ell_1$represents the effect of investor psychological biases on share price volatility for individual company listed in NSE. Given that $\mu_{i,t} = (\mu_{i,t}, \mu_{i,t}, \ldots, \mu_{N,T})$ are residuals which are normally distributed with zero mean and variance-covariance matrix (ψ_t) and there is enough information in the stock market up to time (t-1) which informed ($\mu_{i,t}$), then, (ψ_t) is time dependent. On inserting the psychological biases variables, Equation 3.5 is extended to Equation 3.5 as follows

$$SP_{i,t} = \rho_i + \sum_{k=1}^{p} \omega_k \, SP_{i,t-k} + \ell_1 \mathrm{OC}_{i,t} + \ell_2 LA_{i,t} + \ell_3 MA_{i,t} + \mu_{i,t} \ldots \ldots \ldots \ldots \ldots \ldots (3.6)$$

Where $SP_{i,t}$is the model dependent variable (share price volatility), $SP_{i,t-k}$ is one period lag of share price volatility, while OC, LA and MA denotes overconfidence, loss aversion and mental accounting respectively as the main The rest of the parameters are and variables are as described in Equation 3.5.

The conditional variance and covariance of the volatility of the share price is defined in this study as shows in Equations 3.7 and 3.8. The equations also assumes GARCH (1,1) process following the model by (Cermeño & Grier, 2006).

$$\sigma_{i,t}^2 = \emptyset_i + \vartheta\sigma_{i,t-1}^2 + \varphi SP_{i,t-1} + \gamma_1 \mathrm{OC}_{i,t} + \gamma_2 LA_{i,t} + \gamma_3 MA_{i,t} \dots\dots\dots\dots\dots\dots\dots\dots (3.7)$$

$$\sigma_{ijt} = \tau_{ij} + \beta\sigma_{ijt-1} + \epsilon SP_{ij,t-1} + \alpha_1 \mathrm{OC}_{ij,t} + \alpha_2 LA_{ij,t} + \alpha_3 MA_{ij,t} \dots\dots\dots\dots\dots\dots (3.8)$$

Equations 3.6 to 3.8 are the final panel GARCH models which are estimated using likelihood maximization method presented as log-likelihood function. Equations 3.6 to 3.8 can be written in matrix notation which as used to build the likelihood function as follows.

$$SP_{,t} = \partial + Z_{,t}\emptyset' + \varepsilon_{,t} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3.9)$$

The likelihood maximizing model estimated by panel GARCH in this study is as shown in Equation 9.

$$L = -\frac{1}{2}NTln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln|\cap_t| - \frac{1}{2}\sum_{t=1}^{T}[(SP_{,t} - \partial - Z_{,t}\emptyset') \times\cap_t (SP_{,t} - \partial - Z_{,t}) . (3.10)$$

3.8 Model Diagnostics Tests

A number of statistical diagnostic tests were necessary to check the suitability of data for analysis as well as justifying the selection of panel GARCH model as opposed to other panel data model such fixed effect, which can analyze the data collected in this study. As such diagnostic test such stationarity (unit root) test, autocorrelation test, test for pair-wise correlation and heterogeneity and Pesaran test CD corssectional dependency test were employed to test for the data suitability. To avoid spurious regression results, this study employed Augmented Dickey-Fuller test as well as Phillips-Perron test for stationarity in both case seeking to reject the null hypothesis of the two test that the data contains unit roots (non-stationery) at 95% confidence. This was followed by the construction of a correlation matrix, which aimed at testing the compatibility of explanatory variables in a multiple regression model. According to Bakarr and Jalloh (2021) pair-wise correlation between two explanatory variables is considered high if it exceeds 0.8, otherwise it is low and the variables under consideration can be used in a linear regression model without affecting the test power of one another. This was tested in all data groupings as manufacturing and processing unit, service sector and pooled data.

3.81 Stationarity (unit root) test

The first diagnostic test employed by the current study was the panel test for unit root. This test is relevant in any econometric model since it cure the problem of spurious regression results. Spurious regression results arises when the results of an econometric model exhibits a significant relationship between variables although they are meaningless (Kao, 1999) The test for the presence of unit root for the panel data collected was conducted through Phillips-Perron (PP) as well the Augmented Dickey Fuller (ADF) tests. The two test were selected because they widely used in panel data analysis to check whether the data set used is stationery or has unit roots. In particular the ADF test is used to handle complex panel data set that contain multiple time series just like in the current study which combines time series data for various companies to form panel data. The ADF test for unit roots includes the use of high order regressive process which introduces the lags as the regressorsin the model thus in process increasing the robustness. On the other hand PP test uses non-parametric correlation t-test to check the for the process of unit root. Both test provide a null hypothesis that the panel data used in the study is non-stationery while the alternative hypothesis provide for stationery of the data collected. This study sought to reject the null hypothesis in both tests to justify the panel data suitability in the econometric modeling. The two tests for unit root were tested to enhance the robustness of the test since ADF model works best for higher autorehressive processes while the PP test works best under an assumption that the model exhibits heteroscedasticty and autocorrelation in the disturbance term (Chou & Lee, 2003)

3.8.2 Autocorrelation test

The current study also test for autocorrelation in the residual of the of the panel GARCH model estimated. The autocorrelation test is relevant because it helps in analyzing the correlation between different points in time in the residual. The test can also serves as an important tool for prediction movement in financial market between successive periods as well as assessing the randomness and stationery of a time series data (Uyanto, 2020). The Durbin-Watson test was used by the current study test whether the sampling error in the study is the cause of autocorrelation. The test aim at determining if there is correlation between consecutive residual is severe to influence the output. The test provides for a null hypothesis of no autocorrelation among residuals and an alternative hypothesis of autocorrelated residuals. A test statistic (d) which ranges between 0 and 4 is used to interpret results with d = 2 implying no correlation, d< 2 implying a positive autocorrelation between residuals while d>2 signifies a negative correlation. A serious autocorrelation exists if the test statistic is less than 1.5 or greater than 2.5 otherwise for the range of 1.5 <d<2.4, autocorrelation is likely not to be a concern in the model (Kabaila et al., 2021).

3.8.3 Pesaran test CD test

The Pesaran CD test proposed by Pesaran (2004) and later advanced by (Pesaran, 2021) was used to check for the cross-sectional dependency across panels. This test is particularly relevant when dealing with large panels where the cross-sectional units (N) is greater than the time series (T). This suits the current study's data set where 59 companies listed on NSE were examined for a period of 10 years spanning 2014- 2023. The test is relevant as it checks for cross-sectional dependency in estimation residuals of the panel data collected. This may arise due to common economic shock which tend to influence similar firms as well as unobserved components which tend to have simultaneous effect across firms. The Pesaran CD test is based on the averaging paired correlation coefficients of the residual term obtained from individual regression model applied either on a stationery or dynamic heterogeneous panels.

The estimated CD estimator follows the following iteration.

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N=1}\sum_{j=i+1}^{N}\widehat{\rho_{ij}}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.)$$

Equation 3.8 provides for a null hypothesis of no cross-sectional dependency, that is CD estimated is insignificant for $N(0,1)$ and N > T. Unlike other techniques of testing of testing for cross-sectional dependency, such as Langrage Multiplier test, Pesaran CD test has a mean value at zero point of evEry N and T which give rise to disturbance that is symmetrically distributed even when the sample size is relatively small and the data set has (Hoyos & Sarafidis, 2006)

3.8.4. Breusch – Pagan LM

Moreover, it was essential to employ Breusch – Pagan LM test to test for the problem of serial correlation (heteroscedasticity) since the study used of panel data. In case of serial correlation, the model was estimated using the Newey-west robust standard errors, which eliminates the problem of volatility as required by the panel model estimation. The Breusch – Pagan LM test sought not to reject the null hypothesis of constant variance in residuals presented as

$H_0 : \rho_i = \rho_K$ ……………………………………………………………………………..(3.7)

This hypothesis is not rejected H_0, implying that the variances of the error term are constant and that the pooled data can be estimated by both fixed and pooled regression with cross-sectional dummy variables to give consistent results.

3.8.5 Test for ARCH effect

In financial analysis, volatility in price of securities is often characterized by clustered volatility where periods of high volatility are followed by periods of even higher volatility as well as period of very low volatility. This makes the traditional methods of linear models unable to capture these variations hence ARCH family models are recommended because they allow conditional variance of current period to depend on past errors obtained in the analysis (Bouras et al., 2019). The current study employed a panel GARCH model to estimate the relationship between psychological biases and share price volatility among NSE listed firms. To validate this empirical model, it is relevant to test for ARCH effects in the time series in order to tell whether the GARCH model adequately captures the volatility in the securities price. This test was first developed by Engle(2002)who established an empirical model used to check whether the current variation in a given variable is related to the variation in previous period. This is a common phenomenon in financial data. The ARCH effect basically test for the conditional heteroskasticty by looking at the variance of over time especially where volatility clustering is common as in case of financial time series analysis. The test uses a Langrage Multiplier test which regresses the squared residuals of the estimated GARCH model at either lagged or current values. The test has a null hypothesis as there are no ARCH effect (the coefficients of lagged squared residuals is zero) against an alternative hypothesis of presence of arch effect.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

The chapter presents the results and discussion to achieve the three research objectives. The study aimed at determining the effect of loss aversion, mental accounting, and overconfidence on share price volatility among firms listed in the Nairobi Securities Exchange (NSE). The results were categorized into manufacturing and processing (30 companies), commercial services (29 companies), and pooled (all 59 companies) NSE listed companies. The chapter presents data on the test for stationarity test (unit root), pair-wise correlation test and normality as pre-estimation tests. Finally, the chapter provides results and a discussion of the panel GARCH model on the effects of loss aversion, mental accounting, and overconfidence on the share price volatility of the companies listed in the Nairobi Securities Exchange. Three equations are estimated as manufacturing, processing and the pooled data set each containing same number of independent variables. The panel GARCH model was estimated in three forms as mean, variance and covariance equations in each group of countries.

4.2 Descriptive characteristics of the Nairobi Security Exchange listed companies

This section presents the summary of all the variables used in the study. The descriptive statistics included in the study were mean, median, maximum, minimum standard deviation skewness, and kurtosis. These statistics show the measures of central tendency and dispersion of the data. The descriptive statistics were shown for the three categories: manufacturing & processing, commercial services, and pooled NSE-listed companies. The measures of central tendency and dispersion are important in data as they provide information on the distribution of the data (Chakrabarty, 2021). The descriptive statistics of the variables used in the study are presented in Table 4.1. The variables were share price volatility (SPV), which was the dependent variable. The independent variables were overconfidence (OC), loss aversion (LA), and mental accounting (MA) across the three categories, namely manufacturing & processing, commercial services, and pooled. This section presents the descriptive characteristics of the variables used in the study.

The data used was obtained from NSE listed companied from 2014 to 2023. Out of the 63 listed companies in the NSE, only 59 were included for statistical analysis. A company was included in the study if it had data for at least four years. It is noteworthy that, in some years, information was missing, thus resulting in unbalanced panel data.

Table 4.1: Descriptive statistics

Statistics	Manufacturing and Processing			
	[#]SPV	LA	MA	OC
Mean	0.4153	-1.563	0.2381	42.219
Median	0.4022	-1.465	0.1716	26.774
Maximum	0.9967	1.546	1.0519	177.281
Minimum	0.0982	-5.877	0.007	5.728
Std. Dev. [@]	0.1456	1.2119	0.226	41.395
Skewness	0.8168	-1.0866	2.0052	1.919
Kurtosis	4.7668	6.4721	6.3979	5.6499
Jarque-Bera[$]	48.251	139.81	230.24	181.27
Probability	<0.001	<0.001	<0.001	<0.001
	Commercial services			
Mean	0.3766	-1.253	0.0936	31.999
Median	0.3402	-1.057	0.4446	22.088
Maximum	0.9177	2.949	0.9516	180.184
Minimum	0.1454	-6.424	0.001507	5.135
Std. Dev.	0.1413	1.5758	0.1614	32.4924
Skewness	0.8843	-0.8389	3.4367	2.6641
Kurtosis	3.3534	4.9659	15.4652	10.2274
Jarque-Bera	39.311	80.722	2448.4	974.25
Probability	<0.001	<0.001	<-0.001	<-0.001
	Pooled			
Mean	0.3915	-1.3300	0.1383	35.839
Median	0.37138	-1.166	0.0665	23.420
Maximum	0.9966	2.949	1.0518	180.184
Minimum	0.0982	-6.424	0.0015	5.135
Std. Dev.	0.1442	1.4416	0.2033	36.7825
Skewness	0.8631	-0.9388	2.6743	2.3196
Kurtosis	3.9634	5.5841	9.7458	7.7955
Jarque-Bera	79.904	208.31	1513.2	908.96
Probability	<0.001	<0.001	<0.001	<0.001

[#]SPV is the share price volatility, OC overconfidence, LA loss aversion, and MA mental accounting

[@]Std. Dev.

[$]Jarque-Bera represents the Jarque-Bera test

Table 4.1 presents the descriptive statistics of the four variables used in the study across the three categories. For manufacturing & processing companies, the mean SPV was 0.4153±0.1456 with a minimum of 0.0982 and a maximum of 0.9967. The data had a median of 0.3402. Further, the findings showed that the SPS had a skewness of 0.8168 and a kurtosis of 4.7668. Regarding the LA, the mean was -1.563±1.211873 with a minimum and maximum of -5.877 and 1.546, respectively. The data had a median of -1.465. The descriptive statistics revealed a skewness and kurtosis of -1.086456 and 6.472168, respectively. The mean and median for MA were 0.23805±0.2260 and 0.1716, respectively. Manufacturing and processing companies listed in NSE had a minimum and maximum of 0.007 and 1.0518. Further, the skewness and kurtosis were 2.0052 and 6.3978, respectively. Concerning overconfidence, the descriptive statistics revealed a mean and median of 42.219±41.395 and 26.774, respectively. The variable had a minimum and maximum of 5.728 and 177.281, respectively. Skewness and kurtosis were 1.919 and 5.649. The overall results showed that the data was normally distributed. This suggested that the SPV, LA, MA, and OC variables did not have significant variation from the expected mean for manufacturing and processing NSE-listed companies. The results suggested that SPV, LA, MA, and OC could be used for further analysis.

Table 4.1 shows that the Commercial services NSE listed companies had a mean SPV of 0.3766±0.1413, a median of 0.3402 with a minimum of 0.1454, and a maximum of 0.9177. The skewness and kurtosis were 0.884364 and kurtosis 3.3534. The mean and median of the LA of the commercial services NSE listed companies were -1.253±1.575802 and -1.057, respectively. The commercial service NSE listed companied had a minimum and maximum LA of -6.424 and 2.949, respectively. The descriptive statistics revealed a skewness and kurtosis of -0.8389811 and 4.966, respectively. The mean and median for MA for commercial NSE-listed companies were 0.093652±0.1614 and 0.4446, respectively. The minimum and maximum MA of the commercial NSE-listed companies were 0.0015 and 0.9517, respectively. Further, the skewness and kurtosis were 2.0052 and 6.3979, respectively. Regarding the OC of the commercial services NSE listed companies, the mean and median were 31.999±32.49242and 22.088, respectively. The variable had a minimum and maximum of 5.135 and 180.184, respectively. Skewness and kurtosis were 2.6642and 10.22747. The results for the commercial services NSE listed companies SPV, LA, MA, and OC were normally distributed. The findings indicated that SPV, LA, MA, and OC could be used for further analysis.

Table 4.1 shows that the mean and median SPV of all the 49 NSE-listed firms included in the study were 0.39149±0.1442 and 0.3714, respectively. The minimum and maximum SPV were 0.09816 and 0.9967, respectively. Also, skewness and kurtosis were 0.8639 and 3.9634, respectively. The 49 companies listed in the NSE had a mean and median LA of 1.3300±1.4416 and -1.166, respectively. The companies had a minimum and maximum LA of -6.424 and 2.949, respectively. The descriptive statistics revealed a skewness and kurtosis of -0.9388038 and 5.5841, respectively. The mean and median for MA for the 49 NSE-listed companies were 0.138309±0.2033 and 0.0665respectively. The minimum and maximum MA of the NSE-listed companies were 0.0015 and 1.0519, respectively. The company showed skewness and kurtosis as 2.6743 and 9.7458, respectively. The 49 NSE-listed companies had a mean and median OC of 35.839±36.78254 and 23.420, respectively. The variable had a minimum and maximum of 5.135 and 180.184, respectively. Skewness and kurtosis were 2.3197 and 7.7955. The results suggested that the NSE-listed companies' variables SPV, LA, MA, and OC had a normal distribution. Overall, the findings indicated that SPV, LA, MA, and OC could be used for further analysis.

From all groups of companies, it can be noted that the standard deviation of volatility of the share price is low in each case below the mean value implying that the volatility of share prices for the companies listed in the NSE is low and are suitable for investment. On the other hand, from this table it can be noted that the standard deviation of loss aversion is high greater than the average value implying greater perception of loss out of investment on stock market as compared the anticipated gains. Similarly, the data shows a high variability in the mental accounting, and overconfidence as compared to manufacturing companies. These differences implies heterogeneity in the data collected which makes panel data models, suitable for analysis. The model assumes that specific variable effect do not influence the independent variables in the model hence robust results (Alexander & Lazar, 2021).

The variables across the three categories were subjected to the Jarque-Bera test to assess whether the variables were normally distributed or not. The analysis was to test whether the variables SPV, LA, MA, and OC across manufacturing & processing, commercial services, and pooled have a normal distribution with unspecified mean and variance. Therefore, the Jarque-Bera test was evaluated at a 5% significance level.

Table 4.1 shows the manufacturing and processing NSE listed companied had SPV (JB=48.251, p<0.0001), LA (JB=139.81, p<0.001), MA (JB=230.24, p<0.001) and OC (JB=181.27, p<0.001). The commercial services NSE listed companies show the SPV (JB=39.311, p=0.009), LA (JB=80.722, p<0.001), MA (JB=2448.4, p<0.001), and OC (JB=974.25, p<0.001). Finally, all the 49 NSE listed companies show an SPV (JB=79.904, p<0.001), LA (JB=208.31, p<0.001), MA (JB=1513.2, p<0.001) and OC (JB=908.96, p<0.001). Jarque-Bera test results showed that all the variables were statistically significant at p=0.05. Therefore, the null hypothesis that the data was not normally distributed was rejected. Therefore, the variables were appropriate for further analysis.

The trend plot to illustrate the movement of the study variables over time can be visualized as shown in Figure 4.1.

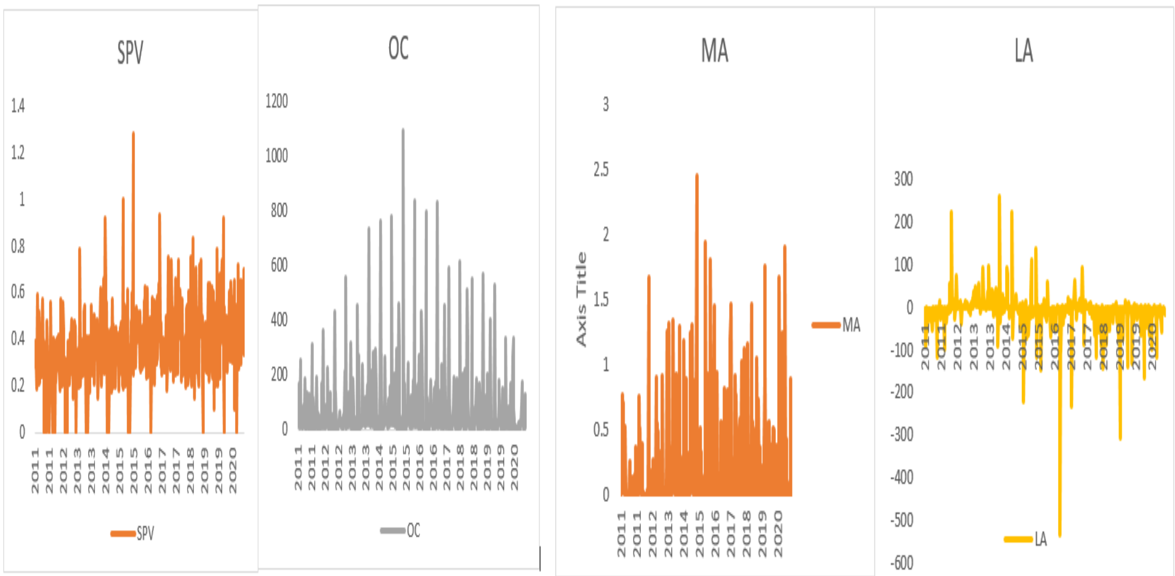

Figure 4.1 Trend analysis of the study variables

From this analysis it can be noted that the variable under consideration have very high variations over time and across the firms. For instance, share price volatility and loss aversion exhibits almost a similar trend in up and downward movements implying that the variables exhibits a positive correlation. On the other hand overconfidence and mental accounting exhibits only a positive fluctuation. In particular the variation in level of overconfidence level is high with the highest level being over 100 while and least level being below 5 units. This is the similar scenario for mental accounting. Very high volatility exhibited by the study's variable implies high degree of risk and uncertainty which can be best analysed by the use of GARCH family models

4.3 Model diagnostics

The panel data was subjected to a diagnostics test to ascertain whether the data was suitable for regression analysis. The tests conducted included the unit-root tests (Augmented Dickey-Fuller test and Phillips-Perron test), pair-wise correlation and heteroscedasticity (Breusch-Pagan (BP) Test), this section presents the model diagnostics.

4.3.1 Panel-data unit-root tests

Unit root tests were implemented to assess whether the variables used in the study were stationary. The findings showed that all the variables across the three categories of manufacturing & processing, commercial services, and pooled NSE-listed companies were stationary (Table 4.2).

Table 4.2: Unit root Test of the study variables

Variable#	Method	Manufacturing and Processing		Commercial services		Pooled		Interpretation
		Statistics	p-value	Statistics	p-value	Statistics	p-value	
SPV	ADF+ - Fisher Chi-square	-4.4425	0.01	-5.6673	0.01	-7.6721	0.01	Stationary
	PP $- Fisher Chi-square	-8.4491	0.01	-7.5201	0.01	-23.877	0.01	Stationary
LA	ADF - Fisher Chi-square	-4.8814	0.01	-6.1505	0.01	-7.3049	0.01	Stationary
	PP - Fisher Chi-square	-12.498	0.01	-16.344	0.01	-22.298	0.01	Stationary
MA	ADF - Fisher Chi-square	-4.4748	0.01	-5.7682	0.01	-8.5852	0.01	Stationary
	PP - Fisher Chi-square	-7.1877	0.01	-12.527	0.01	-21.882	0.01	Stationary
OC	ADF - Fisher Chi-square	-2.3138	0.01	-4.6968	0.01	-8.727	0.01	Stationary
	PP - Fisher Chi-square	-5.9344	0.01	-10.802	0.01	-19.468	0.01	Stationary

#SPV is the share price volatility, OC overconfidence, LA loss aversion, and MA mental accounting

+ Augmented Dickey-Fuller Test

$ Phillips-Perron te

The p-value across the variables was p=0,01, which was significant at p= 0.05. Therefore, the variables had no unit root problem. All the variables across the categories were stationary, as shown by the significant p-value for ADF - Fisher Chi-square and PP - Fisher Chi-square (Table 4.2).

4.3.2 Correlation Test

Pair-wise correlation was estimated to determine the association between the variables used in the study. The pair-wise correlation was run for all three categories. Pair-wise correlation is an essential diagnostic test as it helps reveal relations of interest between variables (Gregorich et al., 2021). High pair-wise correlation between independent variables means that the model estimated would be inefficient because the highly correlated variables would affect the test power of each other.

Table 4.3 presents the correlation matrix of the dependent variable (SPV) and independent variables (LA, MA, and OC) across the three categories. The correlation between variables in this study was implemented to test for Multicollinearity. Multicollinearity is a state where variables used in a regression model are highly correlated (Reddy & Balasubramanyam, 2021). The multicollinearity test is essential as it shows how the independent variables can be used to describe the dependent variable. Multicollinearity is evident when two independent variables are highly correlated, thus making it difficult to ascertain the individual influence of each variable in the dependent variable.

Table 4.3: Pair-wise correlation of the study variables

	Manufacturing and Processing			
Variable [#]	SPV	OC	LA	MA
SPV	1			
OC	-0.1111***+ (<0.001)	1		
LA	0.0761*** (<0.001)	0.0437(0.6)	1	
MA	0.3581*** (<0.001)	0.2232*** (<0.001)	-0.0310 (0.7)	1
	Commercial services			
	SPV	OC	LA	MA
SPV	1			
OC	-0.2206*** (<0.001)	1		
LA	0.0380*** (<0.001)	0.2317**[$](0.028)	1	
MA	0.2982*** (<0.001)	0.2305*** (0.005)	-.0149(0.9)	1
	Pooled			
	SPV	OC	LA	MA
SPV	1			
OC	-0.1111*** (<0.001)	1		
LA	0.0761*** (<0.001)	0.0437(0.619)	1	
MA	0.3581*** (<0.001)	0.2232*** (<0.001)	-0.0395(0.668)	1

[#]SPV is the share price volatility, OC overconfidence, LA loss aversion, and MA mental accounting

[+]*** significant at 1% level of significance.

[$]*** significant at 1% level of significance.

The presented values are correlation coefficient (r) and p-value in parenthesis.

Table 4.3 showed that the highest correlation between independent variables was 0.2232 for manufacturing & processing, 0.2305 for commercial services, and 0.2232 for the pooled data. The correlation coefficients were less than 0.5, suggesting that the data had no multicollinearity problem. The low correlation coefficient suggested that the data could be subjected to regression analysis without collinearity problems. Therefore, the three independent variables, LA, MA, and OC, were not highly correlated and thus retained for regression analysis.

4.3.3 Heteroscedasticity test

The Breusch-Pagan (BP) test assesses heteroskedasticity in linear regression and assumes that error terms are normally distributed (Breusch & Pagan, 1979). Therefore, the BP test determines the existence or absence of heteroskedasticity. The BP tests the null hypothesis that the residuals are distributed with equal variances implying that the error term is constant and the data under consideration is homoscedastic. The alternative hypothesis on the other hand provides that the data is heteroscedatsic Heteroscedasticty in the model makes the variance of the estimators to be biased and unreliable since it is not minimum leading to wrong conclusion of either to reject the null hypothesis where it should be rejected.

This test uses the chi-squared test statistic's p-value to either affirm or reject the null hypothesis based on the level of significance selected. For instance, the p-value of chi-squared test below 0.05 provides an evidence for the rejection of the null hypothesis and conclude that the data used the analysis is homoscedastic.

Table 4.4: Breusch-Pagan (BP) Test

Category	Breusch-Pagan (**BP)**	**P-value**	**Decision**	**Conclusion**
Manufacturing and Processing	10.257	0.9633	Do not reject H_0	Heteroscedasticity is not present.
Commercial services	8.796	0.8543	Do not reject H_0	Heteroscedasticity is not present.
Pooled	11.47	0.9784	Do not reject H_0	Heteroscedasticity is not present.

Significance at p=0.05

Table 4.4 showed that the p-values of the Breusch-Pagan (BP) test manufacturing and processing (p=0.9633), commercial services (p=0.8543), and pooled (p=0.9784) all greater than critical values hence were not significant at p=0.05. Given that the p-value was greater than p=0.05, the null hypotheis was not rejected leading to a conclusion that the errors are free from heteroscedasticity problem. Therefore, the data is suitable for the regression analysis as it guarantees minimum variance and reliable results.

4.3.4 Autocorrelation Test

The Durbin-Watson test assesses the existence of autocorrelation in regression output (Durbin & Watson, 1950). The test is used to detect autocorrelation in the residuals of linear models. The model is used to test for the null hypothesis (H0) that the residuals of the time series linear correlation model are uncorrelated. The Durbin-Watson value ranges between zero to four, with a value of 1.5 to 2.5 showing the existence of no autocorrelation (Osemeke et al., 2024).

Table 4.5 Durbin Watson Test

Category	Durbin Watson (DW)	P-value	Decision	Conclusion
Manufacturing and Processing	1.923	0.3732	Do not reject H0	No autocorrelation.
Commercial services	1.832	0.3642	Do not reject H0	No autocorrelation.
Pooled	1.957	0.3852	Do not reject H0	No autocorrelation.

Significance at p=0.05

Table 4.5 shows that the Durbin Watson value of 1.923 and p=0.3732 for Manufacturing and Processing NSE-listed companies. The Commercial services NSE listed companies had a Durbin Watson of 1.832 and p=0.3642. Finally, the 49NSE-listed firms had a Durbin Watson value of 1.957 and p=0.3852. Therefore, we accept the null hypothesis that there was no multicollinearity in the data. Thus, the data can be used for regression analysis.

4.3.4 Pesaran CD test for cross-sectional dependency

Pesaran CD test was used to check for the cross-sectional dependency a cross panel error, the test follows from estimation a dynamic panel model then after which the Pesaran CD test statistic and probability values are estimated. The obtained results provided the test CD test statistic of 0.2035 and probability value of 0.671 which is greater than the probability value (0.05) at 5% level of significance hence the decision of failing to reject null hypothesis was made. The null hypothesis of weak cross-sectional dependancy a cross errors imply that the panel data collected can be pooled since they have homogenous slope parameters. The homogeneity in the parameter coefficients assures efficiency gains in out of pooling data and estimating panel models as compared to running individual OLS models across individual cross-section. The Pesaran CD test conducted in this study thus guarantees improvement in model efficiency when panel GARCH model is estimated to investigate the effect of psychological biases on volatility of share prices in NSE listed firms.

Table 4.6 Pesaran test for cross-sectional dependency

H0: The errors have weak cross-sectional dependency	
Pesaran CD test statistic	0.2035
Probability value	0.671
Decision using 5% level of significance	Do not reject null hypothesis

4.3.5 Normality test

The current study also did the normality test to investigate the fit of the GARCH model and ascertain how likely it is the variables under consideration are normally distributed. The normally test is based on the assumption that the error terms of the regression model is normally distributed. To this effect, the Shapiro-Wilk as well as Jarque-Bera test normality test were employed. Both Shapiro-Wilk and Jarque Bera ttest have the probability value greater than 0.05 at 0.0571 and 0.4533 implying that the regression residuals do not departure from the normality. Hence the regression residuals are normality distributed and can give efficient estimates free from statistical biases related to non-normality residuals.

Table 4.7 Normality test

Test	Chi (2)	Z-statistics	Probability value
Shapiro-Wilk test		2.547	0.0571
Jarque-Bera test	4.222		0.4533

4.4 Panel GARCH model

Although heteroskedasticity and autocorrelation for the data has been tested, and found to satisfied, it was necessary for this study to justify the selection of panel GARCH model as the main estimation model. The justification entailed testing for the presence of ARCH effects using ljung-box q test which checks for the presence of conditional heteroskedasticity and serial correlation in residuals. The test sought to reject the null hypothesis that for any specified number of lags, the data generating series has no autocorrelation (Lee & Valera, 2016). This test follows an ARMA model fitting where autocorrelation of the residual terms is estimated.

The null hypothesis is rejected in presence of zero or very low autocorrelation implying that the model significantly fits the ARMA fitting. Table 4.8 shows the ljung-box q test results for the three groups of data as manufacturing and processing, commercial and pooled data.

Table 4.8 Test for conditional heteroskedasticity and serial correlation in residuals (ARCH effects test)

Category	Ljung-box q (4)	**ARCH(4)**
Manufacturing and Processing	0.136	7.6332**
Commercial services	0.213	23.6421*
Pooled	0.557	15.8154***

Note +***,** and * imply significance level at 1%, 5% and 1% level of significance.

From this table it can be noted that both ARCH and Ljung-box tests are generated using the fourth order autoregressive residuals' lag (4). The Ljung-box test provided small correlation coefficients less than 0.6 which implies absence of correlation problem in the residuals. This gives a go ahead to estimate the share price volatility in this study using an autoregressive lagged model. To add on, the ARCH effects test statistics is significant across all groups providing a strong evidence of conditional heteroskedasticity in the share price variances. This justifies the use of GARCH model to capture the time varying volatility of the NSE listed companies over the study period.

Panel GARCH model was used to determine the effect of overconfidence, loss aversion and mental accounting on share price volatility among the NSE-listed companied. The estimated regression model was in three categories as presented in Table 4.9. The first column provides the panel GARCH model using mean, variance and covariance equation while for manufacturing and processing firms while the last two columns consists of the regression output for the commercial firms and the pooled data respectively. Running multiple regression as in Table 4.9 was necessary to investigate the effect of psychological biases on the firms listed in these two sectors as well as to check for the model robustness. Consistency in terms of coefficients' sign, significance and magnitude implies that the estimated results are robust.

For instance negative effect of psychological biases on the volatility of prices is consistent across three regression models as well as the positive effect.

The overall goodness of the fit for the estimated panel GARCH models was tested by the use of log-likelihood function. According to Deniz et al.(2021), the higher the value of log-likelihood statistic the better the fit of GARCH model. The likelihood ratio test equally compares the panel GARCH model specification to see whether it improve the model fit. From the analysis, in Table 4.9 it can be noted that the pooled data set has a highest log-likelihood value at 357.8034 meaning that this model best suits the it GARCH estimation technique (fit). This is due to fact that large data tend to have small margin of error hence more accurate as compares to the small data. The pooled data comprised of the two data set from manufacturing and processing sector as well as commercial sector. From Table 4.9 it can be noted that in the variance equation the coefficient of GARH ($\emptyset$)is highly significant across all the model as compared to the ARCH coefficient implying that the later model does not capture enough variation in price hence the former model is appropriate. Similarly, from the mean equation, the coefficients of the first and second lag of the dependent variable (share price voracity) are statistically significant and positive. This is expect since the micro and macro factors that influence share price can be persistent over time thus spreading effect over longer time. Similarly, this study tested for the poolability of the panel data used in the analysis using Chow test. This test results provides for a null hypothesis of a possibility (no structural breaks) in the estimated regression against an alternative no poolability of the data in regression due to structural breaks. Chow F statistics is used provide the evidence for rejecting the null hypothesis. The Chow test results are found that bottom of Table 4.9 provide an F statists of 4.44 insignificant at 5% hence null hypothesis is not rejected.

Table 4.9 Effects of investor psychological biases on share price volatility: Panel GARCH model

Variable	Manufacturing and Processing	Commercial services	Pooled
Mean equation Coefficients			
$Constant$	.3554***	0.3423**	0.3539***
	(0.000)	(0.001)	(0.000)
SP_{t-1}	.6348***	.5429***	0.5957**
	(0.000)	(0.000)	(0.001)
SP_{t-2}	.0135*	0.067**	0.136**
	(0.067)	(0.018)	(0.048)
OC	-0.2172*	-0.2084**	-0.1093***
	(0.051)	(0.016)	(0.000)
LA	-0.0214**	-0.0046**	-0.0168*
	(0.030)	(0.002)	(0.062)
MA	0.1262	0.0022**	0.0342**
	(0.185)	(0.042)	(0.004)
Variance equation			
$\emptyset$ (GARCH)	0.2313***	0.3613***	0.3017***
	(0.000)	(0.000)	(0.000)
ϑ(ARCH)	0.0886*	0.0672*	0.0447**
	(0.064)	(0.055)	(0.049)
$Constant$	5.5877***	4.8571***	4.1190***
	(0.000)	(0.000)	(0.000)
OC	-0.3177*	-0.1722*	-0.3815**
	(0.067)	(0.071)	(0.048)
LA	-0.1072***	-0.1891***	-0.0469**
	(0.004)	(0.021)	(0.002)
MA	0.0116***	0.2215**	0.0187**
	(0.000)	(0.047)	(0.001)
Covariance equation			
$Constant$	0.0608*	0.0716**	0.0828**
	(0.059)	(0.040)	(0.043)
σ_{t-1}	0.4976***	0.4991***	0.3781***
	(0.000)	(0.000)	(0.000)

SP_{t-1}	5.0033***	4.8161***	5.1237***
	(0.000)	(0.000)	(0.000)
OC	-0.1275***	-0.1980**	-0.1211**
	(0.000)	(0.0008)	(0.001)
LA	-0.2592***	-0.1355***	-0.1439**
	(0.001)	(0.000)	(0.016)
MA	0.1305***	0.1406**	0.0108**
	(0.023)	(0.002)	(0.010)
Log-likelihood	250.5109	312.572	232.5634
Chow F-			4.23*

#OC overconfidence, LA loss aversion, and MA mental accounting

+*,** and *** denote significant at a 10%, 5% and 1% level of significance respectively.

The values show the coefficient estimates and p-values in parentheses.

4.4.1 Effect of Overconfidence on Share Price Volatility in Nairobi Securities Exchange Listed Companies

Table 4.9 shows that the overconfidence had a coefficient of -0.2172, -0.2084 and -0.1093 for Manufacturing & Processing, Commercial services, and pooled model, respectively. The findings suggested that holding other variables constant, increasing overconfidence by 1 unit leads to a decrease in the share price volatility by 0.2172, 0.2084, and 0.1093 for Manufacturing & Processing, Commercial services, and Pooled, respectively for the mean equation. Cermeño and Grier (2006) proposes that there is a potential gain when GARCH model is estimated using variance and covariance equation. Hence from the results it can be noted that increase in overconfidence reduces share price volatility by 31.77%, 17.22% and 38.15% for the manufacturing and processing, commercial and pooled categories respectively for the variance. The covariance equation on other hand provides that a unit increase in the overconfidence reduces share price volatility by 0.1275, 0.1980 and 0.1211 for manufacturing and processing, commercial and pooled data respectively. The potential gain can be expressed in terms of coefficient size for the variance equation and significance level for the covariance equation.

The sign was negative across the three categories and equations, suggesting that the relationship between overconfidence and share price volatility was strongly negative. This suggested an inverse relationship between overconfidence and share price volatility in NSE listed Companies. The p-values across the three categories were p<0.001, which was less than p=0.05. In comparing the categories of listed companies, this study reveals that overconfidence has a greater effect on lowering the share price volatility among the manufacturing and processing as compared to the commercial services listed companies. This because overconfidence often lead to irrational behaviours where investors tend to buys stock even at higher prices with an anticipation that the price will continues to rise. This stabilizes the demand for hence leading to low price volatility especially among manufacturing and processing farms where there is a perception that the demand for consumables will always be high (Trejos et al., 2019). The negative relationship between overconfidence and share price volatility across all the groups of firms contradicts the self-attribution and overconfidence theory which provides that traders tend to associate positive outcomes to their owns skills while associating the negative once to the external factors such as bad luck.

The findings of the current study are consistent with that of Lawa et al. (2021) who found that managerial overconfidence (Tobin-Q) had a significant positive effect on price share. The findings suggested that the significant effect of managerial overconfidence on share price was a result of managerial biases on companies' values. Further, Sharawi (2023) revealed that overconfidence plays an important role in price share in Egypt. The author found that CEO's overconfidence had a significant effect on the share price collapse. The study revealed a positive and significant effect of CEO's overconfidence on share price collapse. Equally, the findings support the study by Kuranchie-Pong and Forson (2022) who employed GARCH (1,1) and GIR-GARCH (1,1) to analysis the role of overconfidence biases in stock volatility in Ghana. In this study overconfidence played a crucial role in minimizing the stock volatility especially during the COVID period since traders had confidence in performance of stock market after the pandemic. Lastly the current study findings are consistent with Bouteska and Regaieg's (2018) who found that overconfidence has a significant negative effect on the performance of service companies. More so, the findings revealed that investors tend to have more overconfidence in decision-making. This suggested that there existed a negative relationship between overconfidence and performance.

On other hand, this study contradicts the findings of Mushinada and Veluri(2020) while analysis the relationship between overconfidence, self-attribution and stock market volatility in India. This study revealed a positive correlation between market volatility which explains a large a symmetric volatility in Indian stock volatility between April 2004 and March 2012. This had earlier been found by Metwally and Darwish(2015) which examined the evidence of overconfidence biases in the Egyptian stock market between 2002 and 2012. In this study the effect of overconfidence on securities market volatility was positive when first lag of overconfidence, it then turned to negative at second lag and later turned positive at third lag which persists until the fifty lag. This study's findings are in line with self-attribution and overconfidence theory which provides that overconfidence tend to have a positive effect on volatility of the share price especially when it is upward.

4.4.2 Effect of loss aversion on Share Price Volatility in Nairobi Securities Exchange Listed Companies

Table 4.9 shows that loss aversion had negative coefficients as -0.0214, -0.2084, and -0.1093 for Manufacturing & Processing, Commercial services, and Pooled, respectively in the mean equation. These findings suggested that holding other variables constant, increasing loss aversion by 1 unit led to a decrease in the share price volatility by 0.0214, 0.2084, and 0.1093 for Manufacturing & Processing, Commercial services, and Pooled, respectively. The sign was negative across the three categories, suggesting that the relationship between overconfidence and share price volatility was strongly negative. For the variance and covariance equations, an increase in loss aversion in the former model reduces share price volatility by 0.1072, 0.1891 and 0.0469 among the Manufacturing & Processing, Commercial services, and Pooled, respectively. From the later model a unit increase in loss aversion is associated with 0.2592, 0.1355 and 0.1439 reduction in share price volatility for Manufacturing & Processing, Commercial services, and Pooled, respectively. This suggests an inverse relationship between loss aversion and share price volatility in NSE listed Companies. The negatives relationship between these variables can be due to the fact that mental counting tend to make investors see money as less exchangeable than really it is. This leads them to become susceptible to financial biases such as sunk cost fallacy which makes investors not to early leave one company for another even when it is clear that the shift in investment option would be beneficial (Hogrebe & Lutz, 2024)

The findings on loss aversion and share prices revealed by this study are consistent with Adiputra et al. (2024), who found that loss aversion has a significant and negative effect on financial and investment decisions. The findings were attributed to the application of loss aversion and mental accounting in risk management, thus reducing the financial and investment decision-based risks. Similarly, Xia and Madni (2024)found that loss aversion was an important variable in predicting price movement. The study revealed that mental accounting significantly influenced investment success in China. To add on, Bouteska and Regaieg(2020) also found out a negative relationship between loss aversion and return on assets in the US stock market.

According to Yang, (2019), a loss aversion tend to either have a downward or an upward relationship share price volatility because it affects the investors attitude by inducing more pain related to loss than the joy associated with gains. This makes an investor to be reluctant to trade-off between uncertain higher yield stock and lower gain stock which is secure. This explain why most investors prefer to put their money in low yield treasury bills that are secure (guarantees return) than invest in higher yield stock which often lead to loss of value. Similarly, given that investors are naturally risk averse, their optimal decision is always a sluggish response to change which especially emanate from external environment hence a negative relationship between loss aversion and stock price volatility. On the other hand, Yang(2019) also proposes that in a dynamic setting loss aversion among investors can lead to time varying risks which often generate excess share price volatility hence affecting how much a stock holder is likely to earn if they choose to invest in risky stocks.

4.4.3 Effect of mental accounting on Share Price Volatility in Nairobi Securities Exchange Listed Companies

In analysing the effect of mental accounting, this study found that the variable has positive coefficients of 0.1652, 0.1522, and 0.1542 for Manufacturing & Processing, Commercial services, and Pooled, respectively under the mean equation. The findings suggested that Ceteris paribus, increasing mental accounting by one unit, leads to an increase in the share price volatility by 0.1262, 0.0022, and 0.034 for Manufacturing & Processing, Commercial services, and Pooled, respectively in the mean. For the variance equation, this study found that 100% increase in mental accounting increases share price volatility by 1.16%, 22.15% and 1.87% for the Manufacturing & Processing, Commercial services, and Pooled, respectively. The covariance equation on the other hand reveals that a unit increase in the risk aversion increases share price volatility by 0.1305, 0.1406 and 0.0108 for the Manufacturing & Processing, Commercial services, and Pooled, respectively.

The sign was positive across the three categories, suggesting robust positive relationship between mental and share price volatility. The findings indicated that mental accounting has significant effect on the share price volatility of the in mean equation among Manufacturing & Processing firms while for commercial and pooled data the variable is significant at 10% only. For the covariance and variance equation loss aversion was found to have positive significant effects across all data groups implying an enhancement of the GARCH estimation as proposed by Cermeño and Grier(2006).

This study's findings are in line with Bouteska and Regaieg (2018) who revealed that mental accounting exerts a positive effect on the performance of companies in the US market. Suggesting that mental accounting significantly influenced the performance of companies in the US.

On the other hand, the findings of the current study contradicts those Bertella et al. (2022) who found that mental accounting had a negative effect on the trading volume implying that that an increase in loss aversion led to a decrease in volume of trade.Similar to this study, Ainia et al. (2019) found that mental accounting does not influence investment decisions. The findings suggested that mental accounting had a no significant effect on investment decisions. This implied that a person's low or high mental accounting does not affect their investment decision.

4.5 Summary

This study sought to investigate the effect of investor psychological biases on the share price volatility of NSE-listed companies. The panel GARCH model which estimates the mean, variance and covariance equations was used as the main econometric model. The data for the study was collected from 59 companies and categorized into three classes, namely Manufacturing & Processing (30), Commercial services (29), and Pooled (59). The data of each category was subjected to a series of analyses. First, descriptive statistics were performed, which included the mean, median, standard deviation, maximum, and minimum. A test for normality was done using the skewness, kurtosis, and Jarque-Bera tests.

Similarly, before actual panel GARCH regression analysis, the data was subjected to diagnostic tests to check the suitability of the data for estimating a multiple regression. The diagnostic tests performed included a unit root test, autocorrelation test, pair-wise correlation, heteroscedasticity test, and Ljung-box q test for ARCH effect in the model. The findings showed that the data had no multicollinearity problem, the variables were stationary, and the data had no autocorrelation as well as heteroscedasticity. On the other hand the ARCH effects test failed to reject the null hypothesis implying that the effects were present. This study estimated three model using on the data groupings as mean, variance and covariance equations and presented the findings as in Table 4.9. The variance and covariance equations in the panel GARCH model were estimated due the fact that they are more robust and efficient as compared to the mean equation estimated under GARCH model (1,1) (Cermeño & Grier,. 2006)

Table 4.10 Summary of the hypothesis testing

Hypothesis	Manufacturing & Processing			Commercial services			Pooled		
	Sign	**Significance**	Decision	**Sign**	**Significance**	Decision	**Sign**	**Significance**	Decision
H_{01}: Overconfidence has no significant effect on the share price volatility of NSE-listed companies.	-ve	Significant	H_0 Rejected	-ve	Significant	H_0 Rejected	-ve	Significant	H_0 Rejected
H_{02}: Loss aversion has no significant effect on the share price volatility of the NSE-listed companies.	-ve	Significant	H_0 Rejected	-ve	Significant	H_0 Rejected	-ve	Significant	H_0 Rejected
H_{03}: Mental accounting has no significant effect on the share price volatility of NSE-listed companies.	+ve	Significant	H_0 Rejected	+ve	Significant	H_0 Rejected	+ve	Significant	H_0 Rejected

NSE Nairobi Security exchange

+ve positive

-ve negative

H0 null hypothesis

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Introduction

The chapter highlights the conclusions based on the study objectives and lastly presents the study recommendations based on the objectives followed by suggestion of areas for future research.

5.2 Summary of the findings

The study investigated the effect of investor psychological biases on share price volatility of the NSE listed companies across the Manufacturing & Processing, Commercial services, and Pooled. The study's findings revealed that investor psychological biases influence the volatility of share prices of the NSE-listed companies. This study was based on the hypothesis that investor psychological biases influence share price volatility. The investor psychological bias variables employed by the study were overconfidence, loss aversion, and mental accounting. In the specific objectives, this study determined whether overconfidence, loss aversion, and mental accounting significantly affect the share price volatility of NSE-listed companies using a sample of 59 companies.

The finding revealed overconfidence and loss aversion had negative and significant effect on the volatility of share prices across all groups Manufacturing & Processing, Commercial Services, and Pooled. On the other hand, this study found that mental accounting has a positive significant effect on the share price volatility across all the groups. These findings are in support of some previous studies while it also contradicts some studies.

5.3 Conclusion

Overconfidence had a negative and significant effect on volatility among the NSE-listed companies. The findings indicated that overconfidence affected volatility of share prices. Thus, the conclusion is made that overconfidence is an essential investor psychological bias variable when making investment decisions.

Among the NSE-listed companies sampled, loss aversion had a negative and significant effect on the volatility of share price. Thus, the conclusion is that loss aversion is equally a key investor psychological bias variable when making investment decisions which leads to fluctuation in the share prices.

Among the NSE-listed companies, mental accounting positively and significantly influence volatility of share prices. This is observed a cross all the three types of data set implying robustness. Thus, the conclusion is that this is an essential investor psychological bias variable to consider when making investment decisions.

5.4 Recommendations

Based on the study findings, the following recommendations are made;

Given that overconfidence had a negative and significant effect on share price volatility among Manufacturing and Processing, Commercial Services, and Pooled NSE-listed companies, the study recommends that investment consultants and advisors should equip themselves with approaches for monitoring and evaluating investors' overconfidence to enhance performance in the stock markets.

Secondly, given that loss aversion had equally a negative significant effect on share price volatility among Manufacturing & Processing, Commercial Services, and Pooled NSE listed companies, it is considered to be a critical investor psychological bias variable. Therefore, investment consultants and advisors should equally pay more attention to the variable in order to control share price volatility.

Lastly this study found that mental accounting had a positive and significant effect on share price volatility among Manufacturing and Processing, Commercial Services, and Pooled NSE-listed companies. The study recommends that investment consultants and advisors critically analyze the NSE mental accounting biases to guide potential investors in the stock markets effectively.

5.5 Areas of further research

The study focused on the effects of investor psychological biases on the volatility of share prices of NSE-listed companies. The study used three independent variables: overconfidence, loss aversion, and mental accounting. Further studies could consider integrating investors' perceptions of the effects of investor psychological biases on share price volatility using a cross-sectional Survey approach. This would help bridge the knowledge gap by availing literature on these modes as well as addressing previous inconsistencies around psychological biases price volatility.

REFERENCES

Ainia, N. S. N., & Lutfi, L. (2019). The influence of risk perception, risk tolerance, overconfidence, and loss aversion towards investment decision making. *Journal of Economics, Business, & Accountancy Ventura*, *21*(3), 401-413. https://doi.org/10.14414/jebav.v21i3.1663.

Akhtar, F., & Das, N. (2020). Investor personality and investment performance: from the perspective of psychological traits. *Qualitative Research in Financial Markets*, *12*(3), 333–352. https://doi.org/10.1108/QRFM-11-2018-0116

Alan, S., Singh, H., Bhattacharya, S., & Kumar, K. (2016). North American Journal of Economics and Finance Invisible walls : Do psychological barriers really exist in stock index levels ? *North American Journal of Economics and Finance*, *36*, 267–278. https://doi.org/10.1016/j.najef.2016.01.006

Alexander, C., & Lazar, E. (2021). The continuous limit of weak GARCH. *Econometric Reviews*, *40*(2), 197–216. https://doi.org/10.1080/07474938.2020.1799592

Awino, M. H. (2021). *Influence of Board Composition on Performance of Sugar*.

Babaei, H., & H, S. G. (n.d.). *Time-varying dynamics in financial macroeconomics and markets*.

Bakar, S., Ng, A., & Yi, C. (2016). The Impact of Psychological Factors on Investors ' Decision Making in Malaysian Stock Market : A Case of Klang Valley and Pahang. *Procedia Economics and Finance*, *35*(October 2015), 319–328. https://doi.org/10.1016/S2212-5671(16)00040-X

Bakarr Tarawalie, A., & Jalloh, T. (2021). External Debt and Economic Growth Nexus in the Ecowas: A Threshold Analysis. *International Journal of Business and Economics Research*, *10*(5), 178. https://doi.org/10.11648/j.ijber.20211005.13

Barajas, A., Beck, T., Belhaj, M., & Naceur, S. Ben. (2020). Financial Inclusion: What Have We Learned So Far? What Do We Have to Learn? IMF Working Paper Institute for. *IMF Working Paper*, *20*(157). https://www.imf.org/-/media/Files/Publications/WP/2020/English/wpiea2020157-print-pdf.ashx

Bertella, M. A., Silva, J. N., & Stanley, H. E. (2020). Loss aversion , overconfidence and their effects on a virtual stock exchange. *Physica A*, *554*, 123909. https://doi.org/10.1016/j.physa.2019.123909

Bhowmik, R., & Wang, S. (2020). Stock market volatility and return analysis: A systematic literature review. *Entropy*, *22*(5), 1–18. https://doi.org/10.3390/E22050522

Bibi, L. (2021). *Effect of Overconfidence Bias on Investment Decisions: Mediating Role of Risk Perception and Moderating Role of Self-Attribution Bias and Illusion of Control*. https://thesis.cust.edu.pk/UploadedFiles/Lailo Bibi-MMS201020.pdf

Bouras, C., Christou, C., Gupta, R., & Suleman, T. (2019). Geopolitical Risks, Returns, and Volatility in Emerging Stock Markets: Evidence from a Panel GARCH Model. *Emerging Markets Finance and Trade*, *55*(8), 1841–1856. https://doi.org/10.1080/1540496X.2018.1507906

Bouteska, A., & Regaieg, B. (2020). Loss aversion, overconfidence of investors and their impact on market performance evidence from the US stock markets. *Journal of Economics, Finance and Administrative Science*, *25*(50), 451–478. https://doi.org/10.1108/JEFAS-07-2017-0081

Cermeño, R., & Grier, K. B. (2006). *Chapter 10 Conditional Heteroskedasticity and Cross-Sectional Dependence in Panel Data: An Empirical Study of Inflation Uncertainty in the G7 countries*. *8555*(May), 259–277. https://doi.org/10.1016/s0573-8555(06)74010-x

CHAOUDHARY, D. N. (2022). a Study on Investors' Perception Towards Stock Market. *Interantional Journal of Scientific Research in Engineering and Management*, *06*(05), 60–74. https://doi.org/10.55041/ijsrem12897

Cherono, I., Olweny, T., & Nasieku, T. (2019). *Investor Behavior Biases and Stock Market Reaction in Kenya*. *9*(1), 147–180.

Chou, W. L., & Lee, D. S. Y. (2003). Cointegration analysis of audit pricing model: A panel unit root test approach. *Journal of Business Finance and Accounting*, *30*(7–8), 1141–1164. https://doi.org/10.1111/1468-5957.05370

Cushman, F. (2020). Rationalization is rational. *Behavioral and Brain Sciences*, *1*. https://doi.org/10.1017/S0140525X19001730

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *Stata Journal*, *6*(4), 482–496. https://doi.org/10.1177/1536867x0600600403

Deniz, P., Stengos, T., & Yazgan, M. E. (2021). Revisiting the link between output growth and volatility: panel GARCH analysis. *Empirical Economics*, *61*(2), 743–771. https://doi.org/10.1007/s00181-020-01878-4

Elhussein, N. H. A., & Abdelgadir, J. N. A. (2020). Behavioral Bias in Individual Investment Decisions: Is It a Common Phenomenon in Stock Markets? *International Journal of Financial Research*, *11*(6), 25. https://doi.org/10.5430/ijfr.v11n6p25

Engle, R. (2002). New frontiers for ARCH models. *Journal of Applied Econometrics*, *17*(5), 425–446. https://doi.org/10.1002/jae.683

Gupta, A. Das. (2016). *Investors ' Psychological Biases Toward Stock Market Investment with Special Reference to Bangladesh*. *September 2013*.

Haritha, P. H., & Rishad, A. (2020). *S40854-020-00198-X.Pdf*.

Hogrebe, F., & Lutz, E. (2024). The sunk cost fallacy in venture capital staging: Decision-making dynamics for follow-on investment rounds. *Journal of Corporate Finance*, *86*(April 2023), 102589. https://doi.org/10.1016/j.jcorpfin.2024.102589

Hu, G. X., & Wang, J. (2022). A Review of China's Financial Markets. *Annual Review of Financial Economics*, *14*, 465–507. https://doi.org/10.1146/annurev-financial-111620-010537

I Gede Adiputra, Nur Ainun Bangun, & Bella Graceilla. (2024). The Influence Of Financial Socialization, Overconfidence And Mental Accounting On Investment Decisions. *Jurnal Manajemen*, *28*(1), 200–221. https://doi.org/10.24912/jm.v28i1.1792

Iii, V., & Iv, I. (2017). *http://www.ijssit.com Vol III Issue IV, June 2017 ISSN 2412-0294*. *III*(Iv).

Jacob, B., Mahina, N., Muturi, W., & Florence, M. (2018). *Effect of Self-Attribution Bias on Investment in the Rwandan Stock Market*. *18*(2).

Jain, J., Walia, N., & Gupta, S. (2020). *Evaluation of behavioral biases affecting investment decision making of individual equity investors by fuzzy analytic hierarchy process*. *12*(3), 297–314. https://doi.org/10.1108/RBF-03-2019-0044

Kabaila, P., Farchione, D., Alhelli, S., & Bragg, N. (2021). The effect of a Durbin–Watson pretest on confidence intervals in regression. *Statistica Neerlandica*, *75*(1), 4–23. https://doi.org/10.1111/stan.12222

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, *90*(1), 1–44. https://doi.org/10.1016/S0304-4076(98)00023-2

Kraft, M. A. (2018). Interpreting Effect Sizes of Education Interventions Matthew A. Kraft Brown University December 2018. *Brown University Working Paper*, *December*, 1–28.

Kumari, J., & Mahakud, J. (2016). Investor Sentiment and Stock Market Volatility : Evidence from India Investor Sentiment and Stock Market Volatility : Evidence. *Journal of Asia-Pacific Business*, *17*(2), 173–202. https://doi.org/10.1080/10599231.2016.1166024

Kungu, B. W. (2016). *No Title*.

Kuranchie-Pong, R., & Forson, J. A. (2022). Overconfidence bias and stock market volatility in Ghana: testing the rationality of investors in the Covid-19 era. *African Journal of Economic and Management Studies*, *13*(1), 147–161. https://doi.org/10.1108/AJEMS-05-2021-0209

Lalwani, V., Sharma, U., & Chakraborty, M. (2019). Investor reaction to extreme price shocks in stock markets : A cross country examination. *IIMB Management Review*, *31*(3), 258–267. https://doi.org/10.1016/j.iimb.2019.03.004

Lee, J., & Valera, H. G. A. (2016). Price transmission and volatility spillovers in Asian rice markets: Evidence from MGARCH and panel GARCH models. *International Trade Journal*, *30*(1), 14–32. https://doi.org/10.1080/08853908.2015.1045638

Lin, H. (2019). *Extracting information from option prices in the markets*.

Loke, K. H. (2023). *Factors influencing investment decision-making in stock market among millennials in Malaysia*. *May*. http://eprints.utar.edu.my/5669/

Mamtha, D., & Srinivasan, K. S. (2015). Stock Market Volatility – Conceptual Perspective through Literature Survey. *Mediterranean Journal of Social Sciences*, *7*(1), 208–212. https://doi.org/10.5901/mjss.2016.v7n1p208

Mamun, M. A. A., & Hasanuzzaman, M. (2020). No 主観的健康感を中心とした在宅高齢者における　健康関連指標に関する共分散構造分析Title. *Energy for Sustainable Development: Demand, Supply, Conversion and Management*, 1–14.

Metawa, N. (2018). *Impact of behavioral factors on investors ' fi nancial decisions : case of the Egyptian stock market*. https://doi.org/10.1108/IMEFM-12-2017-0333

Metwally, A. H., & Darwish, O. (2015). Evidence of the overconfidence bias in the Egyptian stock market in different market states. *International Journal of Business and Economic Development*, *3*(3), 35–55.

Mohrschladt, H., & Langer, T. (2020). Biased information weight processing in stock markets ☆. *Journal of Empirical Finance*, *57*(April), 89–106. https://doi.org/10.1016/j.jempfin.2020.04.002

Mushinada, V. N. C., & Veluri, V. S. S. (2020). Self-attribution, Overconfidence and Dynamic Market Volatility in Indian Stock Market. *Global Business Review*, *21*(4), 970–989. https://doi.org/10.1177/0972150918779288

Ngure, F. K., Kariuki, P. W., & Mburugu, K. N. (2022). Macroeconomic Factors and Stock Return of Firms Listed at the Securities Exchanges in East Africa. *Webology*, *19*(2), 5526–5543.

Nyamute, W., Lishenga, J., & Oloko, M. (2015). *The Relationship between Investor Behavior and Portfolio Performance at the Nairobi Securities Exchange*. *May*, 548–551.

Ogiemudia, O. A., & Isibor, E. (2021). Testing Weak Form of Efficient Market Hypothesis (EMH) in Nigeria. *Journal of Academic Reseach in Economics*, *13*(3), 155–172.

Olamide, E., Ogujiuba, K., & Maredza, A. (2022). Exchange Rate Volatility, Inflation and Economic Growth in Developing Countries: Panel Data Approach for SADC. *Economies*, *10*(3). https://doi.org/10.3390/economies10030067

Ouma, H. A., & Oluoch, O. (2019). *Effect of Behavioural Biases On Market Performance of Shares of Firms Listed at The Nairobi Securities Exchange*. *2*(6), 9–22.

Özelli, T. (2020). The financial and conceptual foundations of intangible asset manager capitalism. *Journal of Ekonomi*, *05*(November), 29–100. https://dergipark.org.tr/ekonomi

Parveen, S., Satti, Z. W., Subhan, Q. A., & Jamil, S. (2020). Exploring market overreaction, investors' sentiments and investment decisions in an emerging stock market. *Borsa Istanbul Review*, *20*(3), 224–235. https://doi.org/10.1016/j.bir.2020.02.002

Pérez-Espés, C., Oliver, M. C., & D'Ancona, F. C. (2023). Impact of curricular internships in accounting on university students: an empirical study in Spain | Impacto de las prácticas curriculares en contabilidad en los estudiantes universitarios: un estudio empírico en España. *Revista de Contabilidad-Spanish Accounting Review*, *26*(2), 213–228.

Pesaran, M. H. (2021). General Diagnostic Tests for Cross Section Dependence in Panels. *SSRN Electronic Journal*, *1229*. https://doi.org/10.2139/ssrn.572504

Relationship, T. H. E., & Behavioral, B. (2022). *the Relationship Between Behavioral Biases and*.

Rupande, L., Muguto, H. T., & Muzindutsi, P. (2019). Investor sentiment and stock return volatility : Evidence from the Johannesburg Stock Exchange. *Cogent Economics & Finance*, *7*(1), 1–16. https://doi.org/10.1080/23322039.2019.1600233

Silwal, P. P., & Bajracharya, S. (2021). Behavioral Factors Influencing Stock Investment Decision of Individuals. *International Research Journal of Management Science*, *6*(1), 53–73. https://doi.org/10.3126/irjms.v6i1.42339

Schädler, T. (2018). Measuring irrationality in Financial markets. Archives of Business Research, 6(12), 252-259.

Summers, L. H. (1986). Does the stock market rationally reflect fundamental values?. The Journal of Finance, 41(3), 591-601.

Trejos, C., van Deemen, A., Rodríguez, Y. E., & Gómez, J. M. (2019). Overconfidence and disposition effect in the stock market: A micro world based setting. *Journal of Behavioral and Experimental Finance*, *21*(October 2018), 61–69. https://doi.org/10.1016/j.jbef.2018.11.001

Uyanto, S. S. (2020). Power comparisons of five most commonly used autocorrelation tests. *Pakistan Journal of Statistics and Operation Research*, *16*(1), 119–130. https://doi.org/10.18187/PJSOR.V16I1.2691

Wang, Q. (2022). Crude Oil Futures Hedging Strategies During COVID-19 Using VaR-Garch Models. *Proceedings of the 2021 3rd International Conference on Economic Management and Cultural Industry (ICEMCI 2021)*, *203*(Icemci), 1095–1102. https://doi.org/10.2991/assehr.k.211209.178

Weru, G. W. (2019). *Effect of behavioural biases on investment decision for structured products by retail investors at Nairobi Securities Exchange*.

Woo, K. Y., Mai, C., McAleer, M., & Wong, W. K. (2020). Review on efficiency and anomalies in stock markets. *Economies*, *8*(1), 1–51. https://doi.org/10.3390/economies8010020

Xia, Y., & Madni, G. R. (2024). Unleashing the behavioral factors affecting the decision making of Chinese investors in stock markets. *PLoS ONE*, *19*(2 February), 1–18. https://doi.org/10.1371/journal.pone.0298797

Xue, L., Di, H., Zhao, X., & Zhang, Z. (2018). Uncertain Portfolio Selection with Mental Accounts and Realistic Constraints. *Journal of Computational and Applied Mathematics*. https://doi.org/10.1016/j.cam.2018.06.049

Yang, H., Ryu, D., & Ryu, D. (2017). *Investor sentiment , asset returns and firm characteristics : Evidence from the Korean Stock Market Evidence from the Korean Stock Market*. *3523*. https://doi.org/10.1080/10293523.2016.1277850

Yang, L. (2019). *Loss aversion in financial markets*. *8458*(1947), 119–137. https://doi.org/10.22574/jmid.2019.11.005

Yang, M., Al Mamun, A., Mohiuddin, M., Ali Al-Shami, S. S., & Zainol, N. R. (2021). Predicting stock market investment intention and behavior among malaysian working adults using partial least squares structural equation modeling. *Mathematics*, *9*(8). https://doi.org/10.3390/math9080873

APPENDICES

Appendix I: Data Collection Sheet

S/No	Item	Year/Variable	
1.	Average share price	**Year**	**Share price (KES)**
		2011	
		2012	
		2013	
		2014	
		2015	
		2016	
		2017	
		2018	
		2019	
		2020	
2.	Number of shares traded	**Year**	**No. of shares**
		2011	
		2012	
		2013	
		2014	
		2015	
		2016	
		2017	
		2018	
		2019	
		2020	
3.	Number of exchanges	**Year**	**No. of exchanges**
		2011	
		2012	
		2013	
		2014	
		2015	
		2016	
		2017	
		2018	
		2019	
		2020	
4.	Treasury bill rate	**Year**	**Rate**
		2011	
		2012	
		2013	
		2014	
		2015	
		2016	
		2017	
		2018	
		2019	

		2020		
5.	Dividend paid	**Year**	**Dividend (KES)**	
		2011		
		2012		
		2013		
		2014		
		2015		
		2016		
		2017		
		2018		
		2019		
		2020		

Appendix II: The Nairobi Security Exchange Listed Companies Considered in the Study

S/No	Company	Category
1	ABSA	Commercial services
2	ARM CEMENT	Manufacturing and processing
3	Bamburi cement	Manufacturing and processing
4	BOC Kenya	Manufacturing and processing
5	Britam Holdings	Commercial services
6	British america tobacco	Manufacturing and processing
7	car and general	Manufacturing and processing
8	Carbacid investment	Manufacturing and processing
9	Centum investments	Commercial services
10	Cooperative bank	Commercial services
11	Crown paints	Manufacturing and processing
12	diamond trust	Commercial services
13	E A portlands cement	Manufacturing and processing
14	Ea cables	Manufacturing and processing
15	EAGADS	Manufacturing and processing
16	East african breweries	Manufacturing and processing
17	Equity group	Commercial services
18	Eveready east africa	Manufacturing and processing
19	Express kenya	Commercial services
20	HF group plc	Commercial services
21	Jubilee holdings	Commercial services
22	Kakuzi plc	Manufacturing and processing
23	Kapchrus tea	Manufacturing and processing
24	Kcb	Commercial services
25	Kengen	Commercial services
26	Kenya airways	Commercial services
27	Kenya orchards	Manufacturing and processing
28	Kenya power	Commercial services
29	Kenya Re	Commercial services
30	Liberty kenya holdings	Commercial services
31	Limuru tea	Manufacturing and processing
32	Mumias sugar	Manufacturing and processing
33	Nation media	Commercial services
34	NCBA	Commercial services
35	Olympia capital holdings	Commercial services
36	Safaricom	Commercial services
37	Sameer Africa	Commercial services
38	Sanlam kenya plc	Commercial services
39	sasini	Manufacturing and processing
40	Stanbic holdings	Commercial services
41	Standard chartered	Commercial services
42	Standard group	Commercial services

43	Total kenya	Commercial services
44	Tps eastern africa	Commercial services
45	Transcentury plc	Commercial services
46	Uchumi supermarkets	Commercial services
47	Unga group	Manufacturing and processing
48	williamson tea	Manufacturing and processing
49	Wpp scang group	Commercial services

Source: https://www.nse.co.ke/listed-companies/

Appendix III: Research gaps

Author	Study	Findings	Gaps
Bertella et al. (2020)	Loss aversion, overconfidence and trading volume in artificial stock exchange	Loss aversion had a negative effect on trading volume	The study used regression analysis. This research will use dynamic panel random effect model
Jain et al. (2020)	Influence of loss aversion on investment decision of individual investors in Punjab, India.	Loss aversion was among the most influential factors that determined decision making of individual equity investors, leading to changes in share prices in the stock market.	The study applied Fuzzy analytic hierarchy. The current study will use dynamic panel random effect model to analyze data from NSE.
Ouma & Oluoch (2019)	Behavioral biases effect on performance of shares in NSE	Descriptive analysis found that mental accounting significantly determined share performance in NSE	The study measured share performance using share returns and employed descriptive analysis. The present study will measure share price volatility using standard deviation and will employ dynamic panel random effect model.

Weru (2019)	Effect of overconfidence bias on investment decisions by investors at NSE	Overconfidence had no effect on investment decisions by individual investors	The study used investors primary data and adopted correlation and regression analysis. This study will use dynamic panel random effect model to analyse three psychological; biases.
Lawa et al. (2021)	Determining the Effect of Managerial Overconfidence on Share Price: Evidence from Some FTSE / JSE Top 40 Index Companies	The findings reveals that investment cash flow sensitivity increases price volatility while the marginal overconfidence was seen to increase cash flow sensitivity among firms.	This study did employed panel fixed effect model marginal effect of overconfidence on share price volatility however, it did not look at other determinant of share price volatility such as mental accounting and loss aversion on share price volatility.