THE ROLE OF INVESTOR'S SENTIMENTS IN STOCK RETURNS: EVIDENCE FROM PAKISTAN STOCK EXCHANGE LISTED FIRMS

By

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NATIONAL UNIVERSITY OF MODERN LANGUAGES

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DEDICATION

I dedicate this PhD thesis to Almighty Allah, the Most Gracious and the Most Merciful, whose blessings, guidance, and strength have carried me through every stage of this academic journey.

With deep gratitude, I dedicate this doctoral research to my beloved parents, Mr. Haji Muhammad Iqbal and Mrs. Asia Iqbal, whose unconditional love, prayers, and sacrifices have been the foundation of my every achievement. Thank you for always believing in me.

My heartfelt dedication also goes to my husband, Mr. Irfan Kareem, whose patience, encouragement, and unwavering support have been a constant source of strength and motivation. Your faith in me and your quiet sacrifices made this journey possible. I am forever grateful.

May Allah bless you all abundantly!

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ABSTRACT

This study investigates the impact of investor sentiments on stock returns in the Pakistani equity market, along with the effect of stock return volatility and the lead-lag relationship between sentiment indicators and returns. This research is the first to study investor sentiment proxies rather than a joint index with some novel proxies, i.e. share mispricing, bond yield spread, and gold bullion in the context of Pakistan. Unlike prior research that commonly uses a composite sentiment index, this study employs disaggregated sentiment proxies to capture distinct dimensions of investor psychology, which enhances precision in identifying their individual effects. This study uses panel data of 49 non-financial firms, taken quarterly from 2012-2019, covering 1464 observations of the unbalanced panel. The Fully Modified Ordinary Least Square model, Granger Causality Test and Vector Autoregressive Model are used in the study for hypotheses testing. The results support seven of nine hypotheses, covering all investor sentiments' proxies: share mispricing, bond yield spread, gold bullion, consumer confidence index, turnover, advance-decline ratio and relative strength index. However, the hypothesis related to stock return volatility is rejected. Granger causality tests indicate a mixed lead-lag relationship, with unidirectional and indecisive patterns for some proxies. The VAR model further reveals significant lagged and directional effects of sentiment indicators on stock returns, confirming a dynamic lead-lag relationship. These findings align with existing literature from both developed and emerging markets. The policy implications are threefold: investors can optimize risk-return outcomes by incorporating sentiment signals; financial institutions may enhance risk assessment and product design; and policymakers can leverage sentiment analysis to stabilize markets. Despite data and methodological constraints, this study provides a novel lens into behavioural finance in Pakistan, offering a foundation for future research on investor psychology in frontier markets.

Keywords: investor sentiments, stock returns, noise traders, rational investors, share mispricing, bond yield spread, gold, turnover, technical indicators

Jel Classification: C23, D03, D53, G12, G14

TABLE OF CONTENTS

THESIS/DISSERTATION AND DEFENSE APPROVAL FORM ii
CERTIFICATE OF AMENDMENTS iii
DECLARATION FORM iv
DEDICATION v
ACKNOWLEDGMENT vi
ABSTRACT vii
TABLE OF CONTENTS viii
LIST OF TABLES xii
LIST OF ABBREVIATIONS xiii
CHAPTER 1 1
INTRODUCTION 1
1.1 Background of the Study 1
1.2 Research Problem 3
1.2.1 Background of Problem 3
1.2.2 Problem Statement 6
1.3 Research Objectives 7
1.4 Research Questions 7
1.5 Significance of the Study 8
1.6 Scope of the Study 9
1.7 Organization of the Study 9
CHAPTER 2 12
LITERATURE REVIEW 12
2.1 Theoretical Review 14
2.1.1 Investor Sentiments Theory 14
2.1.2 Expectations Theory 17
2.1.3 Mental Accounting 17
2.1.4 Rational Expectations Theory 19
2.1.5 Market Breadth Theory 20
2.1.6 Momentum Theory 21
2.1.7 Prospect Theory 22
2.1.8 Cognitive Biases 23
2.1.8.1 Overconfidence Bias. 23
2.1.8.2 Loss Aversion. 24

2.1.8.3 Herd Behaviour. 25
2.1.8.4 Framing Effect.. 26
2.1.8.5 Anchoring Bias.. 27
2.1.8.6 Recency Bias. 27
2.2 Empirical Review 27
2.2.1 Stock Returns 28
2.2.2 Investor Sentiments 31
2.2.2.1 Share Mispricing and Stock Returns. 34
2.2.2.2 Bond Yield Spread and Stock Returns. 36
2.2.2.3 Gold Bullion and Stock Returns... 38
2.2.2.4 Consumer Confidence Index and Stock Returns......................... 40
2.2.2.5 Turnover and Stock Returns. 42
2.2.2.6 Advance-Decline Ratio and Stock Returns. 44
2.2.2.7 Relative Strength Index and Stock Returns................................ 45
2.2.3 Firm-Specific Determinants of Stock Returns 47
2.2.3.1 Sales Growth and Stock Returns. 47
2.2.3.2 Financial Structure and Stock Returns. 48
2.2.3.3 Firm Size and Stock Returns. 49
2.2.4 Macro-Economic Determinants of Stock Returns 50
2.2.4.1 Inflation and Stock Returns. 50
2.2.4.2 Interest Rate and Stock Returns. 50
2.2.4.3 Unemployment and Stock Returns. 51
2.2.5 Stock Return Volatility 52
2.2.6 Lead-Lag Relationship 53
2.3 Schematic Diagram of Conceptual Framework 55
2.4 Research Gap.. 57
CHAPTER 3 62
RESEARCH DESIGN AND METHODOLOGY 62
3.1 Research Philosophy 62
3.2 Research Approach 64
3.3 Research Design 65
3.4 Research Strategy 65
3.5 Time Horizons 66
3.6 Sampling Technique 66

3.7 Population 67
3.8 Sample Design 67
3.9 Data Collection Techniques 68
3.10 Data Collection Methods 68
3.11 Operationalisation of Variables 69
3.11.1 Dependent Variable 69
3.11.2 Independent Variables 71
3.11.3 Control Variables 80
3.11.4 Stock Return Volatility 84
3.12 Data Collection and Analysis Procedure 84
3.13 Data Analysis Statistical Methods and Software 89
3.13.1 Cointegration Relationships 89
3.13.2 Fully Modified Ordinary Least Square Analysis 90
3.13.3 Lag Length Selection Criteria 93
3.13.4 Granger Causality Model 94
3.13.5 Vector Autoregressive Model 95
CHAPTER 4 97
RESULTS AND FINDINGS 97
4.1 Diagnostic Testing 97
4.1.1 Descriptive Analysis 97
4.1.2 Diagnostic Testing of the Variables 103
4.1.3 Multicollinearity Test 105
4.1.4 Autocorrelation Test 109
4.1.5 Heteroscedasticity Test 110
4.1.6 Endogeneity Test 110
4.1.7 Cointegration Test 111
4.2 Estimation of Models 112
4.2.1 Investor’s Sentiment and Stock Returns 112
4.2.2 Firm-Specific Fundamental Variables and Stock Returns 118
4.2.3 Macroeconomic Variables and Stock Returns 119
4.2.4 Stock Return Volatility and Stock Returns 120
4.2.5 Lead-Lag Relationship of Investor Sentiments and Stock Returns 121
4.2.5.1. Lag Length Selection Criteria. 121
4.2.5.2. Granger Causality Test 122

4.2.5.3. Vector Autoregressive Model 125
4.3 Robust Analysis 132
CHAPTER 5 137
DISCUSSION AND ANALYSIS 137
CHAPTER 6 152
CONCLUSION, IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS. 152
6.1 Conclusion 152
6.2 Implications 153
6.2.1 Theoretical Implications 153
6.2.2 Policy Implications 156
6.2.3 Practical Implications 158
6.2.4 Research Implications 158
6.3 Limitations 160
6.4 Future Research Directions 162
REFERENCES 165

LIST OF TABLES

Table 4.1: Descriptive Statistics.....98
Table 4.2: Unit Root Test.....104
Table 4.3: Correlation Matrix.....107
Table 4.4: Variance Inflation Factors.....108
Table 4.5: Durbin Watson Test.....109
Table 4.6: Heteroscedasticity Test.....110
Table 4.7: Endogeneity Test.....111
Table 4.8: Cointegration Test.....112
Table 4.9: Unit Root Test of Error term.....113
Table 4.10: Error Correction Mechanism.....114
Table 4.11: Panel Regression Results for Stock Returns.....115
Table 4.12: Lag Order Selection Criteria.....121
Table 4.13: Granger Causality Test.....123
Table 4.14: Vector Autoregressive Model.....125
Table 4.15: Robust Analysis.....133

LIST OF ABBREVIATIONS

AAII	American Association of Individual Investors
ADF	Augmented Dickey-Fuller
ADR	Advance-Decline Ratio
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CCI	Consumer Confidence Index
CPI	Consumer Price Index
DW	Durbin-Watson
EMH	Efficient Market Hypothesis
ETFs	Exchange Traded Funds
FMOLS	Fully Modified Ordinary Least Square
FPE	Final Prediction Error
GFC	Global Financial Crisis
HQIC	Hannan-Quinn Information Criterion
IRC	Investor Risk Compensation
JSE	Johannesburg Stock Exchange
KIBOR	Karachi Inter-Bank Offering Rate
LR	Likelihood Ratio
OLS	Ordinary Least Square
PRISMA	Preferred Reporting Items for Systematic Reviews
PSX	Pakistan Stock Exchange
RSI	Relative Strength Index
SBP	State Bank of Pakistan
VAR	Vector Autoregressive Model
VIX	Volatility Index

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

In recent years, investor sentiment has increasingly been recognised as a critical factor shaping stock market movements worldwide. Global financial markets have witnessed sharp fluctuations that cannot always be explained by changes in economic fundamentals alone. Events such as the COVID-19 pandemic, geopolitical tensions, and rapid technological advancements have amplified the role of market psychology, with fear, optimism, and uncertainty often driving asset prices. These dynamics have highlighted that investor sentiment can significantly influence trading behaviour, liquidity, and short-term volatility, making it an essential area of study in modern finance.

At the same time, the growth of social media platforms, online trading communities, and digital news outlets has accelerated the spread of market sentiment across borders. Retail investors, in particular, are now able to access and respond to information almost instantly, contributing to herding behaviour and sudden market swings. Episodes such as the GameStop rally in the United States, or the sharp sell-offs triggered by viral news during the pandemic, illustrate how investor sentiment can dominate market outcomes even in the absence of strong fundamental signals. This global backdrop demonstrates why analysing the role of sentiment in stock returns has become both timely and relevant.

Beyond isolated events, international evidence consistently shows that investor's sentiments play a non-trivial role in explaining asset price fluctuations. Studies have documented how sentiment indices; such as consumer confidence, investor optimism, and media-based measures; can predict short-term returns and volatility across both developed and emerging markets (Baker & Wurgler, 2007; Smales, 2017). The global financial crisis of 2008 and the COVID-19 crisis both reinforced that market downturns and recoveries are shaped not only by hard data such as GDP or earnings, but also by the prevailing confidence or pessimism of market participants.

Within this context, examining investor sentiment in emerging economies becomes even more important. While developed economies typically have strong regulatory frameworks, transparent disclosure requirements, and active institutional oversight, many developing economies face challenges such as weaker investor protection, limited enforcement capacity, and significant informal sector activity. The existence of a large shadow economy in countries like Pakistan complicates the transmission of fundamentals into stock prices, as unreported financial flows and informal trading practices reduce transparency and create space for speculative behaviour. Such conditions amplify the influence of investor sentiment because price formation is less strictly tied to fundamentals and more susceptible to behavioural and mood-driven dynamics.

Against this backdrop, the Pakistan Stock Exchange (PSX) offers a particularly interesting case. The PSX is widely acknowledged to be concentrated, with trading activity and market movements often dominated by a few large institutional investors, business conglomerates, and family-owned groups. These “big giants” exert considerable influence on price discovery, often overshadowing the actions of smaller investors. Yet, despite this concentration, retail investor participation; although smaller in value; remains highly sentiment-driven. This duality raises important questions about the relative power of institutional dominance versus the collective mood of smaller market participants in shaping returns. Episodes of speculative bubbles and sharp corrections in Pakistan’s stock market history, such as the 2005–06 boom and subsequent crash, were strongly linked to waves of optimism and pessimism rather than to changes in economic fundamentals.

Furthermore, regulation in the PSX reflects the broader challenges of developing economies. Regulatory authorities, such as the Securities and Exchange Commission of Pakistan (SECP), have made strides in strengthening oversight, enhancing disclosure requirements, and promoting transparency. However, enforcement gaps, market manipulation risks, and insider trading concerns remain persistent challenges. This contrasts with developed markets, where mature regulatory institutions, robust enforcement mechanisms, and sophisticated investor bases limit the influence of sentiment and speculation on long-run returns. In developing markets like Pakistan, relatively weaker regulatory capacity allows investor sentiment to play a more pronounced role in driving short-term volatility and mispricing.

The motivation for this study thus stems from two key aspects. At the international level, behavioural finance research increasingly acknowledges that sentiment plays a crucial role in explaining short-term market fluctuations, volatility, and anomalies. At the national level, Pakistan's unique market environment is characterized by a large shadow economy, dominance of a few powerful players, and relatively weaker regulatory enforcement. It provides fertile ground to test the relevance and impact of investor sentiment. Studying this issue not only contributes to academic literature but also offers practical insights for regulators and policymakers on how behavioural factors interact with institutional structures in shaping stock returns.

1.2 Research Problem

1.2.1 Background of Problem

In finance, capital market efficiency is one of the most widely researched and essential topics. The investigation to improve investment strategies depends on the pricing behaviour of the secondary market. Financial analysts, investors, speculators, and regulators are concerned with the behaviour of the stock market. However, the stock market behaviour is explained by how efficient the market is. Fama (1970) explains that market efficiency is a situation where stock prices reflect all available information. Market efficiency theory is significant in finance, with various definitions provided by scholars like Beaver (Vickrey & Bettis, 2001), Rubinstein (Rubinstein, 2001), and Black (Mauboussin, 2002). However, the definition of Fama (Jarrow & Larsson, 2012) is widely acknowledged among scholars. Market efficiency is determined by information and operational efficiency in stock markets. Stock markets play crucial role in directing limited economic resources to productive use. Numerous empirical studies (Jarrow & Larsson, 2012; Mauboussin, 2002; Rubinstein, 2001; Vickrey & Bettis, 2001) have debated market efficiency. The role of stock markets in economic development is significant, Tung & Marsden (1998) report contradictory outcomes related to market efficiency.

Brown (2011) argues that disagreements in exploring the efficient market hypothesis (EMH) result in failures to forecast growth and determine stock prices accurately. Researchers attribute this discrepancy to particular sectors and industries, each with unique accounting policies and methods. These differences make it difficult for researchers, analysts, and investors to draw cross-sectional conclusions about specific industries. Systematic indices are hard to identify across market sectors because investment analysts often specialize in specific sectors or industries. Researchers, financial experts, and regulators have strived to improve capital market investment decisions for years. Numerous studies have been conducted to clarify stock market behaviour for informed investment decisions (Bae & Joo, 2021; Beaver *et al.*, 2020; Baker *et al.*, 2018; Black, 1986; Fama, 1970; Johnson & So, 2018; Rubinstein, 1975; Siriopoulos, 2021; Sutejo & Utami, 2020). Additionally, some research addresses the shortcomings of existing models. Despite varying opinions among financial economists regarding the determination of stock behaviour by EMH and its significant implications for investment policies and economic theories, studies related to EMH validity suggest global acknowledgement. However, uncertainty persists among financial economists about the truth of EMH, especially in emerging markets.

This uncertainty has led to the rise of behavioural finance, a novel field in financial research. Behavioural finance challenges the assumption of rational expectations, providing an alternative explanation for market phenomena. In the contemporary era, financial economists are trying to understand how human psychology influences investors' financial decisions. This field addresses concerns that traditional finance struggles to explain. Behavioural finance research is based on two main assumptions, summarized by Shleifer & Summers (1990): some investors are irrational, leading to mispriced stocks, and arbitrage is limited, expensive, and risky. Noise trader sentiments present systematic risks, affecting asset price equilibrium. These noise traders act on non-fundamental signals, driving prices away from fundamental values. Rational arbitrageurs can only partially eliminate mispricing due to arbitrage limits and risk aversion.

De Long *et al* (1990) reinforce the role of investor sentiments in the financial market. In their model, noise trader decisions are based on risk-averse arbitrageurs and sentiments. Rational arbitrageurs face two kinds of risks: investor sentiments and fundamental risks. These risks can deter arbitrageurs from taking action, causing prices to deviate from their fundamentals. Additionally, other factors limit arbitrage, such as the duration of arbitrage investments, the ownership of the currency used in arbitrage (De Long *et al*., 1990; Shleifer & Summers, 1990), etc. This model argues that investors are normal humans influenced by psychological biases and sentiments, leading to decisions in inefficient markets. They also have different expected returns than risk differences (Singh *et al*., 2021). Behavioural finance factors can better explain stock market movements and decision-making by investors who react to good or bad news, loss aversion, herd behaviour, etc. These behaviours create inefficiencies in stock market information, limiting the applicability of conventional finance theories (De Long *et al*., 1990).

Herbert Simon's ground-breaking psychological research (1955, 1979) reveals that decision-making is influenced by limited rationality and that people often make systematic mistakes in their thought processes (Simon, 1955, 1979). As a result, theories evolved to explore how investors handle risk and uncertainty, such as Kahneman & Tversky's Prospect Theory. This theory suggests that investors focus on gains and losses rather than final wealth and exhibit loss aversion, prioritizing avoiding losses over seeking gains (Kahneman, 1979). Additionally, individuals tend to rely on intuition and emotions over complex reasoning, intertwining their behaviour with the dynamics of financial markets. Considering this, the impact of investor sentiments on the mispricing of securities becomes increasingly significant (Glatzeder *et al*., 2010).

In classical finance, generally, there is no room for investor sentiments. However, sentiments play an essential role in the movement of stock returns. Often referred to as market sentiment, this term describes an investor’s emotional or psychological mind-set towards a particular stock. The overall perception of a specific firm's stock held by investors is reflected in stock trading activities and sudden price movements. Investor sentiments are a crucial aspect of behavioural finance theory. The actual value of stock prices is reflected only in efficient markets with complete information available to investors. However, irrational investors play a significant role in determining stock prices (Fisher & Statman, 2000, 2004). Therefore, evidence supporting the inefficiency of financial markets is more compelling than evidence against it (French, 2017). Essentially, investor sentiments refer to expectations about future cash flows and investment risks that fundamental factors cannot explain.

Understanding the relationship between investor sentiments and stock returns requires understanding how investors behave in financial markets. Investors in financial markets exhibit various behaviours influenced by factors such as risk, information availability, and psychological biases. Understanding these behaviours is crucial for understanding market dynamics and making informed investment decisions. By studying investor behaviour, we gain insights into herd behaviour, over-reaction, and under-reaction, which impact stock prices and market efficiency.

In emerging economies like Pakistan, investor sentiments profoundly impact stock returns. Positive sentiments attract domestic and foreign investors, increasing investment and potentially driving up stock prices. Increased stock price further creates positive sentiment, as high stock prices boost investor confidence and attract more capital. Conversely, negative sentiments result in capital outflows and stock price declines. Various factors, such as political stability, economic indicators, and global market conditions influence the volatility of sentiments in emerging economies. Understanding and monitoring these sentiments is crucial for investors operating in emerging economies to make informed investment decisions.

In order to reveal the relation between investor sentiments and stock prices, this study explores the workings of their impact. This research explores this relation using the theoretical frameworks of Ohlson (1995), Chen (2011) and Reis and Pinho (2021), shedding light on the investors' sentiments and their effect on stock returns. Therefore, this research study aims to analyse the impact of investor sentiments on stock returns.

1.2.2 Problem Statement

In an ideal financial system, stock returns are determined by rational expectations based on fundamental factors such as firm performance, macroeconomic indicators, and industry trends. Under the EMH, prices fully reflect all available information, leaving no room for anomalies or mispricing.

However, in practice, financial markets including the Pakistan Stock Exchange (PSX) often deviate from this ideal. Investor decisions are frequently influenced by sentiments, biases, and psychological factors, leading to mispricing, excessive volatility, and inefficiencies in price discovery.

This mismatch between theory and reality reveals a persistent problem: the explanatory power of fundamental factors alone is insufficient to account for observed stock return behaviour. In Pakistan's context, the limited availability of localised sentiment indices, lack of clarity on the role of non-fundamental drivers, and inconsistent empirical findings further compound the issue. Therefore, there is a clear need to investigate how investor sentiments influence stock returns and to identify suitable proxies that can effectively capture these sentiments within the Pakistani market environment.

1.3 Research Objectives

The research objectives of this study are:

1. To analyse the impact of investor sentiments on the stock returns in the Pakistani stock market
2. To analyse the impact of stock return volatility on the stock returns
3. To analyse the lead-lag and causal relation among investor sentiments and stock returns in the Pakistani stock market

1.4 Research Questions

The research questions of this study are:

1. What is the impact of investor sentiments on stock returns in the Pakistani stock market?
2. What is the relationship between stock return volatility on the stock returns in the Pakistani stock market?
3. What is the nature of lead-lag and causal relationship between investor sentiments and stock returns in the Pakistani stock market?

1.5 Significance of the Study

Understanding the relationship between investor sentiments and stock returns is increasingly important in today's complex and behaviourally driven financial markets. While traditional finance theories emphasise rational decision-making, behavioural finance research has shown that psychological biases and market sentiment can significantly influence asset prices, often causing deviations from fundamental values.

This study is significant for the Pakistani context because it introduces novel investor sentiment proxies: share mispricing, bond yield spread, and gold bullion into the analysis of stock returns in a developing economy. In particular, share mispricing is calculated as the difference between the market price and the intrinsic value, where the intrinsic value is computed using the Benjamin Graham formula. This formula integrates earnings per share (EPS), book value, and other financial fundamentals to provide a comprehensive, objective measure of a stock's valuation. To the best of our knowledge, this Graham-based intrinsic value proxy has never been applied in Pakistani capital market studies, making this approach both innovative and contextually relevant.

By incorporating these proxies, the research not only broadens the scope of sentiment analysis in emerging markets but also offers a more robust and fundamentals-linked measure of investor sentiment. This is particularly important in Pakistan, where the stock market is characterised by high volatility, information asymmetry, and a dominant retail investor base factors that amplify the influence of sentiment over pure fundamentals.

The findings of this study are significant:

For investors: Enhance decision-making, improve timing of entry and exit points, and help in managing portfolio risk during sentiment-driven market swings.

For financial institutions: Support the design of sentiment-sensitive investment products (e.g., thematic funds, sentiment-linked ETFs) and improve risk management through advanced sentiment tracking, potentially leveraging AI.

For policymakers and regulators: Offer tools for monitoring sentiment-induced volatility, developing timely interventions during panic or euphoria, and designing investor education programs to reduce behavioural biases.

Ultimately, this study bridges the gap between investor behaviour and market outcomes in Pakistan's developing capital market, providing actionable insights for improving market efficiency, stability, and attractiveness to both domestic and international investors. The novel integration of Graham's intrinsic value methodology into sentiment measurement not only contributes to behavioural finance literature but also opens new avenues for empirical research in other emerging economies.

1.6 Scope of the Study

This research is limited to studying the KSE-100 index non-financial firms based on FY-2012 of the PSX. All other listed and financial firms are excluded from this study. In addition to it, this research study excludes the crisis era i.e. stock exchange crash in 2007-2008 and COVID-19 in 2020-2021. Moreover, this study uses share mispricing, bond yield spread, gold bullion, consumer confidence index (CCI), turnover, advance-decline ratio (ADR) and relative strength index (RSI) as measures of investor sentiments. In addition to it, this study utilizes sales growth, financial structure and size as firm-specific fundamental variables. However, inflation, interest rate, and unemployment are taken as macroeconomic variables. Other proxies of investor sentiments and other determinants of stock returns are not part of this study. This study uses panel data from 49 non-financial firms taken every quarter from 2012-2019 covering 1,464 observations of the unbalanced panel.

1.7 Organization of the Study

The organization of the chapter-wise thesis on the topic of investors' sentiments and stock returns is structured as literature review, research design and methodology, results and findings, discussion and analysis, and conclusion.

Literature review chapter reviews existing literature on investor sentiments and their impact on stock returns. This chapter covers different theories, models, and empirical studies related to the topic. The theoretical concepts and frameworks that underpin the relation between investor sentiments and stock returns is explored. It also explains how behavioural finance, market efficiency, and investor psychology influence this relation. This chapter also sets hypotheses of the study to empirically test and extract the results to give meaningful outcomes of the data.

Research design and methodology chapter describes the study's research design, data collection method, and sample selection criteria. It also explains how the under-considered study measures investor sentiments and stock returns, and discusses statistical techniques planned to be used. It includes definition and operationalization of 15 variables and the prerequisites of the statistical tools used to test the study hypotheses empirically.

Results and findings chapter presents and analyses the data collected, focusing on the relation between investor sentiments and stock returns. It uses appropriate statistical methods (for instance, fully modified ordinary least square regression results) to support the analysis and to test the set hypotheses. It also sheds light on the reliability of results.

Discussion and analysis chapter interprets the findings from the empirical analysis, compares them with existing literature, and discusses their implications for understanding the impact of investor sentiments on the stock returns. The findings of this study are discussed based on theories related to the behaviour finance.

Conclusion chapter summarizes the study's main findings, discusses their implications, and proposes areas for further research from the perspective of policymakers and investors. Lastly, references include a list of all the sources cited in the thesis, following the appropriate citation style.

In summary, this chapter offers an in-depth examination of the study's background by presenting scholarly evidence related to investor's sentiments and stock returns. From this discussion, the problem is established to examine the relation between investor sentiment and stock returns in the Pakistani stock market. The research problem covers the method for defining research questions and objectives. Additionally, this chapter highlights the significance of this study for stakeholders, policymakers, decision-makers, and market participants in making informed decisions. Lastly, the scope of the study is outlined in terms of delimitations, which are beyond a researcher's control.

CHAPTER 2

LITERATURE REVIEW

The objective of this study is to perform an empirical analysis of the role of investor sentiments in determining stock returns concerning the PSX. This section of the research presents a theoretical and empirical framework, which provides a base for the determination of the research gap and associated hypotheses. Before discussing the theoretical and empirical framework, this chapter provides an overview of the PSX.

Overview of the PSX

The Karachi Stock Exchange (KSE), established on September 18, 1947, is the first stock exchange in Pakistan and one of the oldest in the emerging economies. The Lahore Stock Exchange (LSE) was incorporated in 1974, and the Islamabad Stock Exchange (ISE) followed in 1997. In the early 21st century, Pakistan's KSE-100 Index was recognized by "Business Week" magazine as the world's top-performing stock market index (Sirimane, 2007). In 2005, the World Bank valued listed companies in Pakistan at $5,937 million (World Bank, 2010). However, following the General Elections 2008, political instability, increasing combativeness along the country's western border, rising inflation, and account deficits resulted in a significant drop in the Karachi Stock Exchange, significantly affecting Pakistan's corporate sector. Despite these setbacks, the market substantially recovered in 2009, with positive trends continuing into 2011. By 2014, the KSE 100 Index reached new heights, gaining 907 points (3.1%) and surpassing the 30,000-point milestone. Moody's upgraded its viewpoint on five major Pakistani banks from negative to stable, causing an influx of investments in the banking sector. This improvement was further supported by considerable oil, gas, and cement purchases (Umar, 2014).

To reduce market fragmentation and attract strategic partnerships for technological expertise, the Karachi Stock Exchange merged with the Lahore Stock Exchange and the Islamabad Stock Exchange in January 2016 to form the unified PSX (Dawn.com, 2016). In May 2017, MSCI identified PSX as an Emerging Market rather than a Frontier Market during its semi-annual index review, causing great excitement among traders (Dawn.com, 2017). Consequently, the PSX-100 Index substantially increased by approximately 1.23%, reaching a new peak of 52,387.87 points (Tribune.com, 2017). However, during the fiscal year 2018, there was a negative growth of 7.1% compared to the previous fiscal year, with stocks averaging around 47,000 points (Farooq, 2019). Despite this decline, Pakistan's stock market experienced significant progress during FY2021, with the KSE-100 index rising from 34,889.41 points to 44,262.35 points between July 2020 and April 2021. The PSX successfully navigated through the initial downturn caused by COVID-19, making it the best-performing Asian stock market and the fourth-best worldwide in 2020. Driven by the government's massive stimulus package, a steady central bank policy rate, increased large-scale manufacturing, external account improvements, and reforms introduced by the Securities and Exchange Commission of Pakistan (SECP) and PSX due to COVID-19 circumstances, the PSE-100 Index saw nearly 40% growth during FY2021 (Daily Times, 2021).

In the fiscal year 2021, non-financial companies experienced a significant rise in sales, reaching Rs. 9,521 billion, a notable increase of Rs. 1,465 billion compared to the previous year's decline of Rs. 807 billion. Earnings before interest and tax (EBIT) grew by an impressive 53.21 percent year-on-year during FY21, amounting to an increase of Rs. 433 billion. General, administrative, and other expenses saw comparatively minor growth. Interest expenses decreased from Rs. 299 billion in FY20 to Rs. 224 billion in FY21, leading to an enormous year-on-year profit before taxation increase of Rs. 514 billion. Additionally, the collective profit after tax for all companies soared by Rs. 404 billion, with a year-on-year growth rate of 125.06 percent in FY21 compared to FY20. The net profit margin of all companies rose dramatically to 7.64 in FY21 from 4.01 in FY20 due to remarkable enhancement in private sector companies' net profit margins. Return on assets (ROA) and return on equity (ROE) for all companies increased to 6.37 percent and 17.93 percent in FY21 in comparison to 3.10 percent and 8.91 percent the previous year, respectively (SBP, 2021).

2.1 Theoretical Review

The underpinning theory of this study is investor sentiments theory; however, there are several supporting theories of this study. All the theories are explained as follows:

2.1.1 Investor Sentiments Theory

This theory focuses on the role investor's sentiments in financial markets and stock returns. The theoretical field of behavioural finance analyses investors' sentiments and their influence on stock market activity (Ding *et al*., 2019). Stock market sentiment analysis and investor behaviour are among the methods in finance that help gather data to make informed business decisions. Research shows that in the stock market, price movements correlate with public sentiments related to the companies (Ángeles López-Cabarcos *et al*., 2020).

Investor sentiment research traces back to human psychology, with Watson's pioneering work in 1912 (Watson, 1912; G. Zhou, 2018). Over time, behavioural finance emerged as a discipline that later gave rise to modern investor sentiment theories. Focusing on the psychological aspects of investor behaviour, Prospect Theory (Kahneman & Tversky, 2013) posits that retail investors are more vulnerable to emotional inspirations and cognitive biases, giving rise to irrational trading decisions. Investor's sentiments lack a uniform definition; however, research (Stein, 1996) characterized sentiments as an investor's consistent divergence from the rational expectations for the future. The concept of investor's sentiments aims to assess the market player's anticipation towards their investments. Similarly, scholars (Baker & Wurgler, 2006) describe it as "a belief about future cash flows and investment risks not supported by available evidence." Despite the undeniable significance of investor's sentiments in trading, measuring it is complex as it involves quantifying emotions.

Additionally, varying sentiments may exist among individual investors. Nevertheless, it is widely acknowledged that investor's sentiments are integral to stock market dynamics, providing genuine explanatory power (Baker & Wurgler, 2006, 2007; Ding *et al*., 2019; Zhou, 2018). Sentiments serve as an ambiguous element in economic activities, shaping investors' subjective outlook on future returns. Consequently, this influences their investment behaviours, substantially impacting the overall market.

Investor sentiments theory suggests that investor's collective mood can influence the financial market behaviour to a greater extent than traditional valuation methods. Classical finance theories, such as the efficient market hypothesis, suggest that the markets are rational and always put all the available information. In contrast, the investor sentiments theory explains that irrational behaviours can influence investment decisions. Investor sentiments can also influence market outcomes due to investor's irrational behaviour (Baker & Wurgler, 2007).

The investor sentiments theory and stock turnover are closely interconnected on conceptual and empirical grounds. The stock turnover refers to the ratio of shares traded over a particular time against the average number of shares outstanding. Higher turnover is an indication of active trading; whereas, low trading is suggested by lower turnover. The dimensions of investor sentiments can be used extensively to understand the theory. For instance, overconfidence leads to excessive trading as investors believe they have superior trading skills (Avery & Zemsky, 1998). Thus, when investor sentiments are high, and overconfident, the turnover is more likely to focus on buying and selling (Barber & Odean, 2000).

Baker and Wurgler (2007) describe investor sentiments as either optimism or pessimism regarding stocks in general, as well as an openness to speculate. They identify two main ways investor sentiments influence stock prices: barriers to arbitrage and challenges in company valuation. First, they explain that restrictions on arbitrage differ among stocks while sentiments remain consistent. Second, the overall mood affects the demand for stocks, leading to speculation and different effects across various stocks, even if arbitrage forces are consistent. Both mechanisms impact similar types of stocks. In other words, some assets are more susceptible to speculative demand and thus bear the effects of investor sentiments. Assets that are difficult to value or challenging to arbitrage are ideal targets for subjective decision-making and, consequently, more susceptible to investor sentiments. Generally speaking, these assets tend to be smaller, more unpredictable, young, and non-dividend-paying stocks with high book-to-market ratios. The key is that periods of high or low sentiments result in overpricing or under-pricing sensitive stocks, eventually leading to low or high future returns as prices return to equilibrium (Baker & Wurgler, 2007).

Furthermore, Baker and Wurgler (2006) claim that stock returns with specific features are more vulnerable to sentiment shifts. They discover that size, age, volatility, profitability, dividend distribution, growth, and distress affect a stock's vulnerability to these fluctuations. For instance, young and small stocks are more sensitive to sentiment changes. Although this information is helpful for investors, assessing a stock can be challenging as it requires considering these factors. Therefore, a simple model can be employed to determine the susceptibility of individual stocks to sentiment shifts. As a result, investors can gain insights into a stock's behaviour and use this knowledge to facilitate the stock selection.

Behavioural finance theories propose that investors may adopt wrong beliefs rooted in either excessive optimism or pessimism, leading them to inaccurately assess asset values and cause discrepancies between asset prices and their true worth (De Long *et al.*, 1990; Kumar & Lee, 2006; Lee *et al*., 1991). Eventually, as economic factors become clearer and sentiments fade, mispricing is rectified. This correction results in an inverse relationship between investor sentiments and future stock returns, implying that investor sentiments have predictive power for stock performance.

Investor sentiments can significantly impact financial markets. Existing research attempts to reveal the mechanisms behind this sentiment effect. Chen *et al*. (2013) addressed this dilemma by developing a framework showing that investor sentiments play a role in the importance of accounting information. When investor sentiments rise, people tend to be more optimistic about future earnings growth, and stock analysts are more likely to favor those stocks. Things get even more interesting when investors consider how sentiments influence the expected rate of return, which is a complex relationship. According to pricing theory, the expected rate of return is simply the risk level multiplied by the risk premium. However, optimistic investors might not fully grasp their risk exposure and expect higher rewards for their risk-taking during high-sentiment periods (Jordão *et al*., 2022).

2.1.2 Expectations Theory

The expectations theory suggests that the yield spread between two bonds having different maturities reflects the market's expectations for future interest rates. The theory suggests that the yield spread can be used to gauge market sentiments and expectations related to the direction of interest rates (Hamburger & Platt, 1975). In his research, Begum (2020) examined the expectations theory of the term structures regarding the international bond market using government bonds and treasury bill rates. The expectation theory's relevance to the topic relates to the foundational topic that long-term interest rates have market expectations for short-term rates. For instance, if investors are generally optimistic regarding the economy, they can expect the central bank to raise short-term and long-term interest rates in the future. By doing so, investor sentiments can play a critical role in shaping the expectations that underline the yield curve and influence investment decisions based on those expectations (Baumeister, 2021).

2.1.3 Mental Accounting

The concept of mental accounting has been defined by Özkan and Özkan (2020) s a cognitive process that helps individuals mentally segregate taxes, income, and expenses. Some have separated income from taxes, while others have integrated them. It has been found that investment decisions and personal spending are influenced by mental accounting, and the choices are assessed based on intellectual, emotional, and risk criteria. The theory of mental accounting is a concept in behavioural economics that explains how individuals mentally categorize and assign values to their assets or money based on subjective and arbitrary criteria. It has been described that people create mental accounts for specific goals and expenses, and they make financial decisions based on these accounts instead of the overall financial situation. The behavioural economist Richard Thaler introduced the theory in the 1980s (Thaler, 1980). Since then, it has remained influential in understanding how people manage their finances and investments (Zhang & Sussman, 2017).

The research in this field, as explored in the work of scholars, i.e., Daniel Kahneman and Richard Thaler, shows the role of emotions in investment decisions. Investor sentiments (such as fear and overconfidence), which are emotional biases, can be linked to mental accounting. For instance, an investor with a mental account for retirement savings can be influenced by the emotions related to retirement. Herding behaviour is another aspect where prevailing sentiments influence the investor. Investors might herd into specific asset categories or accounts based on prevailing market sentiments, even if it does not align with their overall financial goals (Abideen *et al*., 2023).

Cherono *et al*. (2019) conducted research in the Kenyan context to explore how investors' behaviour influences the stock market reaction among the listed companies. The investor herd behaviour has been examined along with mental accounting, loss aversion, and overconfidence. The stock market reactions are significantly impacted by overconfidence, loss aversion, and mental accounting in this regard. The use of panel regression is performed in the study on the data collected from 48 companies listed on the Nairobi Stock Exchange between 2004 and 2016.

Bhope (2023) , in his research, explores the effect of the biases of investors on the decision-making skills of female investors in the equity segment. It has been investigated with the help of the study of how behavioural biases can influence decision-making in the Indian equity segment. The opinions of the women were collected with the help of a 5-point Likert scale. Regression analysis has provided insights into investor biases that significantly influence women's decisions in the equity market and shows the role of personality traits in investment choices. The research has been regarded as distinctive by focusing on the risk-averse women investors and conforming the biases regarding their investment decisions.

In their research, Zhang and Sussman (2017) explain the concept of mental accounting in investment decisions and household spending. They discuss how recent advances in Fintech have brought opportunities and challenges to consumers' engagement in mental accounting. These advancements have enabled the detailed tracking of expenses, explicit goal-based savings, and personalized budgeting. Also, automated investment platforms have reshaped financial behaviour, and they urge future research to understand their impact on mental accounting.

Seiler *et al*. (2012) explained the aspects of behavioural finance in real estate investments and discovered significant implications of mental accounting across the disposition curve effect. The study identified various disposition curve shapes. It has been noted that investors are more inclined to sell when transitioning from zero to profitable returns, which also factors in transaction costs.

Drawing from the literature regarding mental accounting and investor behaviour, one can determine that mental accounting can reshape investor sentiments in the gold bullion market. As investors separate income from expenses and taxes, they can mentally categorize gold as a distinct asset within their portfolios. The separation of gold holdings can result in emotional attachments and affect their perception of potential risk and returns. In the gold bullion market, investors' mental accounting process affects their willingness to hold, buy, or sell gold based on the perception of potential risk and returns. In the digital gold market, reshaping investor sentiments is possible because investors categorize and track their holdings to influence their trading decisions. It has been implied that investors are more likely to sell gold when it shows significant price gains, influenced by their mental accounting of gold as a profitable asset (Bradford, 2013).

2.1.4 Rational Expectations Theory

As per the rational expectations theory, it is assumed that individuals have access to all of the relevant information regarding the economy and rationally use it to form their expectations. It implies that people are required to be well-informed and capable of processing complex financial and economic data (Sappideen, 2009). The theory related to the consumer confidence index is rational expectation theory. The theory explains how individuals form their expectations regarding the future based on the available information and make economic decisions accordingly. Primary development of the theory was done in the 1960s and 1970s and has significantly impacted policy analysis and macroeconomic modeling (Ferrer *et al*., 2016).

In terms of stock returns, the rational expectations theory suggests that investors' sentiments are based on proper analysis of economic information, which influences their decisions and potentially impacts the stock returns. It has also been validated by Rashid *et al*. (2022) hat investor sentiments influence the stock market trading, confidence generally increases the trading volume, and pessimism and optimism have mixed effects depending on trading days and model. The research findings have highlighted the complex relationship between rational expectations and emotions in the financial markets.

Another dimension of the rational expectations theory is the adaptive behaviour of the investors since investors are expected to adapt their expectations and beliefs as soon as new information becomes available. Suppose the sentiments of the investors deviate from rationality. In that case, the mispricing of stocks can occur, and it can also impact the returns as the market tends to adjust to such stock price misalignments (Au & Kauffman, 2003). Saldanha *et al*. (2023) have employed the Preferred Reporting Items for Systematic Reviews (PRISMA) methodology for reviewing the factors that influence stock market behaviour under the adaptive market hypothesis. The focus on return predictability has been highlighted. It has been suggested that additional aspects like trading strategy, investor behaviour, location-based methodology, and profitability be considered to improve investor understanding.

2.1.5 Market Breadth Theory

The market breadth theory traces back to the famous TRIN index developed by (Arms, 1989) in 1967 . It focuses on the measurement of weakness or strength of the overall stock market by analysing the number of companies participating in a market on an upward or downward basis. In contrast to the market indices that a handful of large-cap stocks can influence, the market breadth indicators offer a more detailed view of the market sentiments considering the behaviour of several individual stocks (CFITeam, n.d.). The market breadth theory is a counterpoint to the market indices weighted by market capitalization, and a small number of large companies can drive the movements. With a focus on the advance-decline ratio, analysts and investors can get a more holistic view of the market, and a broader range of stocks can be considered. This ratio is considered valuable, particularly for the divergences between actual market health and the market indices (Bloomberg, 2003). The advance-decline ratio is often stated in the context of the market breadth theory. The theory shows a healthy market trend that can be either bearish or bullish and confirmed by the participation of broad stocks in the market. For instance, in a bullish trend, many individual stocks are expected to advance, contrary to the case of a bear trend. The advance-decline ratio is an integral measure of the entire process for validating the breadth of participation (Deng *et al*., 2022).

In specific terms, the market breadth theory complements the investor sentiments theory with the provision of a quantifiable metric that shows the collective mood or sentiments of the participants of the market. A higher degree of advance-decline ratio can signal bullish sentiments. A low ratio can indicate bearish sentiments, and the two can have implications for trading strategies and stock turnover (Bloomberg, 2003). Investor sentiments and market breadth theory are closely related concepts that complement each other in terms of market dynamics.

2.1.6 Momentum Theory

The momentum theory suggests that assets performing well continue to perform optimally, and assets performing not well continue to do the same (Jegadeesh & Titman, 1993). Investors can use the relative strength index to identify and measure momentum while supporting the aspects of technical analysis (Lundström, 2020).

The investor sentiments and the relative strength index are closely related to the momentum theory. As per the theory, it has been suggested that the assets performing well continue doing so, and the ones performing not well also keep doing the same. Investor sentiments play a critical role in this regard, and bullish sentiments play a pivotal role. A downward trend is suggested by the extreme levels of sentiments in this regard. The relative strength index is a momentum indicator that aligns with the theory. The overbought and undersold conditions can show potential reversals in line with the momentum theory and the effect of investor sentiments on market trends (Hill, 2019).

Antonacci (2013) in their research investigated absolute momentum by focusing on the formation period and its effect on bonds, tangible assets, and stocks. Research has demonstrated that absolute momentum is a rule-based and valuable approach for identifying regime changes and enhancing portfolio performance in different applications. As a result, the portfolio performance can be enhanced accordingly in different applications such as stocks, bonds, and other risk parity assets.

2.1.7 Prospect Theory

Stock returns are defined as the profit or loss made by investors after investing in the stocks and when an investor buys a share. There is an inherent anticipation that a profit is made as a result of the price increase. However, there is an equal chance that investors can incur a loss if the price declines. Stock returns are measured in two components: capital gains and dividends. Capital gains are the difference between an asset's purchase price and sale price, whereas dividends are paid on the invested capital. The returns can be termed as realized versus unrealized returns (Lynch, 2004).

The prospect theory is a psychological theory that explains how people make decisions when alternatives involving risk, probability, and uncertainty are presented. The theory holds that people make their decisions based on perceived gains or losses. Given the presence of equal opportunities, most individuals prefer to retain the wealth they already have instead of taking the risk that results in increasing the chances of making a loss (CFI, n.d.).

Stock returns and investor sentiments are closely related in the context of prospect theory. This theory is a behavioural finance concept that has been developed by Daniel Kahneman and Amos Tversky (Kahneman & Tversky, 1979). Regarding prospect theory, investors do not always make rational investment decisions. Instead, they evaluate the potential losses and gains relative to a reference point, often to the purchase price of the stock (Seth & Chowdary, 2017). This reference point influences the perception of risk and reward. When the stock returns are positive, the investors see the gains relative to their reference point, and they tend to become confident and optimistic. The positive sentiments in this context lead to a higher willingness to take risks and result in more aggressive investment decisions. In contrast, when the stock returns are negative, losses are perceived by the investors as their reference point, and they often fear pessimism. The negative sentiments can lead to a perception of risk aversion that can force one to make conservative choices like selling stocks on a premature basis and avoiding new investments (Li *et al*., 2023).

Wang *et al*. (2018) introduce a new perspective using cumulative prospect theory on initial public offerings. The focus was kept on the Chinese initial public offerings between 2006 and 2012, which highlights left skewed IPOs (initial public offerings). The negative skewness tends to have higher first-day returns than the right-skewed ones. The long-term returns are, however, independent of the skewness of IPOs, which leads to a 10.41% higher first-day return for the left-skewed IPOs and attracts more retail orders. Regarding long-term returns, they are independent of skewness for the left-skewed IPOs, but for right-skewed ones, they are inversely related.

López-Cabarcos *et al*., (2020) explore the relation between investor sentiments and behavioural finance. The study has used bibliographic analysis and co-citation analysis to define the theoretical structure and reveal its link to behavioural finance and the theory of efficient markets. The evidence of the study suggests that the significance has been gained by investor sentiments, particularly from 2014, with potential for insights from computer science and mathematical theories in understanding its impact on the stock markets.

Stock returns are influenced by both psychological factors and rational decision-making, as explained by the prospect theory. Investor sentiments critically shape investment choices, with positive sentiments leading to greater optimism and risk-taking, while negative sentiments tend to promote risk aversion and conservative actions. Recent studies have focused on the growing importance of investor sentiments and bridged the gap between traditional market theories and behavioural finance.

2.1.8 Cognitive Biases

2.1.8.1 Overconfidence Bias.

Overconfidence bias is the behavioural principle of overestimating one's abilities, like financial insight (Barber & Odean, 2000). Investors can be misled into thinking that they can beat the market or suffer a higher cost of trading (Iacurci, 2023). It is also known as a tendency to hold misleading and false assessments of talent, skills, and intellect. An investor might think he is better than others. It can be termed a dangerous bias and is very prolific in the behavioural finance markets (Vipond, n.d.)

Share mispricing, sales growth, and overconfidence bias are interconnected aspects that can significantly affect investment decisions. The complexity arises when overconfident investors rely extensively on individual assessments without considering the broader market sentiments. Due to this, investment decisions are disconnected from the collective perception of the market. For instance, investors invest heavily in companies with growth prospects and also fail to recognize the broader market sentiments turning bearish, which requires further corrections for overvaluations (Bouteska & Regaieg, 2020).

2.1.8.2 Loss Aversion.

The theory of loss aversion is a crucial concept in behavioural economics, and it suggests that people are more sensitive to potential losses than gains of equal magnitude. It is the tendency to avoid losses instead of achieving equivalent gains (Kahneman & Tversky, 1979). Loss aversion bias can commonly occur in financial decisions, and people need significant incentives to take financial risks, which can result in a loss. Loss aversion leads to risk-averse behaviour and encourages individuals to avoid situations that result in losses, even if the possible gains are more significant (Aguilar, 2023).

Investor sentiments have a crucial role in a company's financial structure and loss aversion. When investor sentiments are positive, companies can get inclined towards equity financing to exploit favourable market conditions (Bouteska & Regaieg, 2020) to avoid the potential regret of taking debt if the market becomes bearish. In contrast, in terms of pessimistic sentiments, companies show stronger loss aversion by avoiding equity financing as it dilutes shareholders' wealth. Instead, debt financing is selected despite the associated risks. Hence, investor sentiments are influenced by whether the companies prioritize loss aversion or financing structure in their financial decisions (Gal, 2018).

Shafqat and Malik (2021) explore the relationship between risk perception, emotional biases, and trading frequency among individual investors in the PSX. It has been determined that loss aversion and regret aversion negatively influence the trading frequency and moderation of the relationship, which is done by risk perception. The research suggests that emotional biases and risk perception improve the market's capitalization due to training programs. It benefits investors and regulatory bodies like the PSX and the Securities and Exchange Commission of Pakistan.

Investor sentiments influence a company's financing structure, which consists of debt and equity, particularly in the case of loss aversion. Positive sentiments lead to equity financing to avoid potential debt-related regrets in bullish markets, while negative sentiments result in a structure based on debt. Research also shows that emotional biases, market sentiments, and risk perception significantly impact trading frequency and stock returns in emerging economies like Pakistan.

2.1.8.3 Herd Behaviour.

Herd behaviour arises as investors mimic their peers rather than rely on their unique decision-making information (Kyriazis, 2020). Amidst this sea of emotions, irrational investors are persuaded by noise more than complex data. This collective emotional decision-making introduces an added risk layer to be considered – a risk tied directly to investor sentiments (Brown, 1999). In wealth management, herd mentality primarily implies that investors face challenges in accurately predicting market trends due to a lack of adequate information. Consequently, they rely on observing the actions of the masses and continuously strengthen this information, ultimately resulting in herd-like behaviour. Although individual conduct may appear rational in this scenario, it can lead to collectively irrational behaviour (Liu, Liu, & Hen, 2019).

Behavioural finance describes herd behaviour as the tendency of investors and financial market participants to follow the behaviour and actions of a larger group. It is often driven by cognitive biases and emotions instead of rational analysis. It can also result in crashes and market bubbles as individuals make investments on a collective basis, and they make suboptimal investment decisions that are affected by the actions of others. The purpose of behavioural finance is to explain and understand these tendencies in the financial markets (Din *et al.*, 2021)

Herd behaviour, in combination with inflation, can affect investor sentiments on a significant basis. When investors see others making specific investment choices, they follow the same suit even if it contradicts their strategy (Shiller, 1980). This can amplify market trends, which can further result in crashes and bubbles in the market. The value of assets is eroded, and purchasing power is decreased due to inflation. When inflation is high, it can make investors anxious, and they might look for alternative ways to preserve their wealth. The combination of inflation and herd behaviour can result in exaggerated market swings as investors, on a collective basis, flee or flock from assets. This situation is driven mainly by sentiments instead of fundamental analysis (Bikhchandani & Sharma, 2000).

Bogdan *et al*. (2023), in their research, investigate the herd behaviour among individual investors in the crypto currency market, and it is an area where limited research has been carried out. With the use of the cross-sectional absolute deviation (CSAD) model, the analysis of the impact of liquidity and herding sentiments, it has been found that lower liquidity increases herding behaviour across small, medium, and large crypto currencies. Such insights enhance the understanding of the market of crypto currencies and give guidelines for managing associated risks.

Yousaf *et al*. (2018) investigated the herding behaviour in the Pakistan Stock Market from 2004 to 2014, considering different market conditions like falling and rising markets, trading volume, Ramadan effect, and volatility. It has been found that the herding has remained absent during the market fluctuations in times of low trading volume along with the financial crisis of 2007-08 due to information asymmetry and heightened uncertainty. Research also highlights the absence and presence of herding behaviour in specific market conditions, focusing on the role of uncertainty and information asymmetry in influencing investor behaviour, as seen in the case of the Pakistan Stock Market during specific periods.

2.1.8.4 Framing Effect.

The framing effect is a cognitive bias where people's decisions are influenced by how the information is presented instead of the actual content. It shows that how a choice or message is framed can significantly impact decision-making (Kahneman & Tversky, 1979). For instance, a favourable frame can show gains leading to a different decision than a negative frame, highlighting the losses even though the core information is the same. This bias shows the importance of perception and communication in the process of decisions (Yacoub, 2012).

The framing effect and unemployment majorly influence investors' sentiments in a market. The framing effect, based on the information's presentation, influences investors' decisions. The positive frames focus on gains and boost investment and investor confidence. In contrast, negative frames focus on losses, which affect risk aversion and caution (Pompian, 2012). In a similar way, unemployment's impact on investor sentiments is substantial. The higher unemployment results in economic uncertainty, deters investment, and adds to the market's volatility. In contrast, the optimism is fostered by low unemployment and drives investment in such cases. Hence, unemployment and framing effects extensively shape asset prices and market dynamics in the presence of investor sentiments (Dunham & Garcia, 2021).

2.1.8.5 Anchoring Bias.

The anchoring bias is the tendency to believe in the initial reference point, for instance, the starting prices of stock assets, when the investor decides to invest (Kahneman & Tversky, 1979). There are many factors impacting the decision-making of investors, which may include cognitive bias and emotional and sentimental complexity. When investors anchor their perception of a stock’s value to previous prices or historical trends, it leads to biased decision-making, and investors become more sensitive to losses. Investors want to invest in more reliable opportunities outside the stock market. According to investors, gold bullion and bonds are the perfect selection as they think it is a good deal even if they pay a higher price than the stock value (Fajri & Setiawati, n.d.).

2.1.8.6 Recency Bias.

When investors give more weight to recent events or news, it can influence their sentiments and decisions, and they have little association with financial risk tolerance (Silvia, 2021). In the recency theory, the investors remember the recent events, data, and market information, and thus, the decision is made for future stock returns (Kahneman & Tversky, 1979). The financial decisions based on the recency bias lead to significant market fluctuations(Waghmare *et al*., 2021).

2.2 Empirical Review

Numerous research studies have empirically investigated the relationship between investors' sentiments and stock returns. In this context, researchers from developed and developing economies have instigated how sentiments can impact the returns of different kinds of markets. This study examines investor sentiments on the stock returns by measuring sentiments with proxies, i.e., share mispricing, bond yield spread, gold bullion, consumer confidence index (CCI), turnover, advance-decline ratio (ADR), relative strength index (RSI), and some controlling (firm-specific and macroeconomic) variables.

2.2.1 Stock Returns

Stock returns are the profit allocated towards an investor's investment for a particular period, usually one year (Agyemang & Bardai, 2022). The stock returns represent the profit or loss made by an investor from holding shares for a specific period and expressed as a percentage of the initial investment (Mullins, 1982). The investors invest their savings to earn some income from it. This income is in the form of gains earned from trading shares in the stock market or dividends (Reddy & Narayan, 2016). A strong market incorporates new information to make the stock prices and their respective firms precisely valued and stable (Mwangi & Mwiti, 2015). The return on the stock market can predict investment since it is a prospective variable that combines the discounts and expectations of expected cash flows. Stock return plays an index role in investors' decision-making. An investor with a diverse financial capacity can invest in the stock market to ensure that he/she receives a return more than the cost of capital (Agyemang & Bardai, 2022). To assess the performance of the entire stock market, the stock market's return is estimated (Omid *et al*., 2011).

The investigation of the stock market is argumentative as the researchers give undue preference to indices instead of individual stocks in the stock market (Alexeev & Tapon, 2011). Over the years, various academicians have put their efforts into creating and assessing various models for forecasting stock market trends. Some researchers aim to rely on historical stock performance data to make expectations of the future, while others utilize stock indices for predictions. Nonetheless, determining the most effective model for estimating stock market trends remains an ongoing challenge. The stock market represents a platform where public limited company shares are exchanged, enabling everyday individuals to strengthen their investments significantly. It also allows businesses to obtain capital by offering investors a stake in their corporation. Financial theory gives several models related to asset pricing, which associate expected returns with one or more than one variable, signifying numerous risk sources. The characteristics of such variables are based on the models' underlying assumptions. Among these models, the most renowned is the Capital Asset Pricing Model (CAPM), which has one risk source. The second commonly used model is the Arbitrage Pricing Theory (APT), which has numerous risk sources. These models are utilized to examine the performance of funds and to assess the cost of capital (Parab & Reddy, 2020). The models of conventional financial theory are deemed to derive risk factors related to stock price determination. They are based on the assumption that investors have rational expectations, thereby designing their investment strategies, and such strategies are typically founded on the rule of risk and return (Baker *et al*., 1977). These models cannot explain the actual market's performance after internet bubbles and stock market crashes. Several factors influence stock price fluctuations in these models, covering foreign direct investment, price rises, job loss, worker remittances, interest rates, growth rate, supply of currency, and many more (Raza & Jawaid, 2014).

On the one hand, these theories are limited in finding substantial details of long-lasting crashes and bubbles. On the other hand, research studies have brought many studies providing evidence about market inefficiency, irrational participants, and limited arbitrage opportunities. Some investors make trading on noise as though the information is related to fundamental factors (Black, 1986). There is also empirical evidence about the volatility of the stock market and its justification for changes in price in anticipation of dividends. It implies the irrationality of investors and that stock prices are influenced by factors other than fundamental factors (Shiller, 1980). In addition, the emerging field of economic behaviour and behavioural finance has raised questions about EMH. The scholars of this field argue that markets are irrational and driven by greed and fear (Sewell, 2011).

Many factors impact on the stock returns: company performance (Agyemang & Bardai, 2022), economic factors (Sukruoglu & Temel Nalin, 2014), market sentiments (Reis & Pinho, 2021), dividend yield (Kang *et al*., 2017), valuation metrics (Liem & Basana, 2012), risk factors (Venturini, 2022), sector and industry performance (Ranjeeni, 2014), macroeconomic indicators (Sukruoglu & Temel Nalin, 2014), geopolitical risk and global events (Salisu *et al*., 2022), financial policies (Limkriangkrai *et al*., 2017), currency exchange rates (Inci & Lee, 2014), and technological factors (Hirshleifer *et al*., 2013).

Company performance impacts the stock returns through earnings growth and profitability, where positive earnings are linked with higher returns, and companies with solid profitability attract investors (Agyemang & Bardai, 2022). Economic factors impact stock returns in the form of GDP growth and interest rates, where positive growth is linked with higher returns, and lower interest rates decrease borrowing costs, thereby boosting stock returns (Sukruoglu & Temel Nalin, 2014). Market sentiments impact stock returns through investor sentiments and market trends. Positive and negative investor sentiments impact stock returns in the positive and negative trends. Moreover, upward trends and bull markets increase returns (Reis & Pinho, 2021). Divided yield impacts the stock returns in the form of stocks that pay dividends (Kang *et al*., 2017). Valuation metrics impact the stock returns in price-to-earnings ratio and price-to-book ratio. When both ratios are high, it indicates the undervaluation of stock (Liem & Basana, 2012). Risk factors impact the stock returns in the form of volatility and beta.

High volatility is linked with higher expected returns along with higher risk. The stocks with high beta values can experience more significant price movements (Venturini, 2022). Sector and industry performance impact the stock returns in the form of sectoral and industry trends for higher returns (Ranjeeni, 2014). The macroeconomic indicators impact the stock returns through inflation and the unemployment rate. Inflation at a moderate level usually influences stock returns in a favourable perspective (Sukruoglu & Temel Nalin, 2014). The unemployment rate is inverse to stock returns as it contributes to high corporate profits and consumer spending (Sukruoglu & Temel Nalin, 2014). Global economic trends and political stability influence stock returns (Salisu *et al*., 2022). Companies' financial policies about share buybacks, financial management, and capital expenses impact stock returns. In addition, a firm's debt level can impact its risk profile and stock returns (Limkriangkrai *et al*., 2017). The exchange rate fluctuation also impacts on the stock returns of multinational companies (Inci & Lee, 2014). The firms with leading innovation also experience high stock returns (Hirshleifer *et al*., 2013).

The impact of the above-mentioned determinants changes with time and across various market conditions. This study uses investor sentiments and volatility, which influence stock returns. Investors usually utilize a combination of technical analysis, economic analysis, and fundamental analysis to determine these determinants, thereby making informed investment decisions.

2.2.2 Investor Sentiments

Investor sentiments are confidence, belief, disbelief, optimism, or pessimism in investors about the anticipation of company performance. Investor sentiments refer to the investors' collective psychological and emotional outlook, which can influence asset prices and market behaviour. It often oscillates between bearish pessimism and bullish optimism and impacts market trends and investment decisions (Khattak & Siddiqui, 2021). It influences the behaviour of financial markets, driving from an opinion, sustained idea, or thought reflecting the emotional state of a specific circumstance. As a result, the sentiments give an impression of the present economic state beyond contributing to a financial situation for the market behaviour. Behavioural finance covers topics related to investor sentiments beyond firms' fundamentals and macroeconomic factors. Behavioural finance is based on implementing psychology in light of the technological bubble back in 2000 (Pompian, 2012). The prospect theory of Kahneman argues that the emotions of human beings and cognitive errors related to financial decisions determine psychological biases in assessing the prospect performance of stocks, which leads to peak movements and instability (Kahneman & Tversky, 2013). This topic has been debated over the strength and predictability of market bubbles, crashes, or co-movements between the financial markets. The studies carried out in the last decade focus on the movement of financial markets as explained by sentiments, particularly in irrational and unjustified panics or even in the situation of overstated optimism (Benhabib *et al*., 2016; Jitmaneeroj, 2017; Piccione & Spiegler, 2014). Moreover, sentiments are interconnected with emotions (optimistic or pessimistic) to assess investment decisions, influencing asset prices (Benhabib *et al*., 2016; Jitmaneeroj, 2017; Piccione & Spiegler, 2014).

The scale to measure investor sentiment is highly debated by academicians (Zhou, 2018). Sentiment is a latent variable and can only be measured by proxies. Therefore, it is necessary to test the ability of these proxies to assess asset prices since they include unavoidable errors. The prevailing measures of sentiment encompass survey data, market data, and data for text analysis, and the studies are argumentative over the best predictor of sentiment for predicting the movements and co-movements of the market. The survey database measures (Corredor *et al*., 2015; Schmeling, 2009; Zouaoui *et al*., 2011) include University of Michigan Consumer Sentiment Index (Jitmaneeroj, 2017; Spyrou, 2013), the American Association of Individual Investors (AAII), Investors Intelligence, the UBS/GALLUP Index for Investor Optimism (Jitmaneeroj, 2017), the State Street Investors Confidence Index (Jitmaneeroj, 2017), Economic Sentiment Indicator (Simões Vieira, 2011; Spyrou, 2013), the Consumer Confidence Indicator (Chui *et al*., 2010; Fisher & Statman, 2003; Jansen & Nahuis, 2003; Lemmon & Portniaguina, 2006), etc. The market data base measures include closed-end mutual funds (Baker & Wurgler, 2006, 2007), dividend premiums (Baker & Wurgler, 2006, 2007), IPO numbers (Baker & Wurgler, 2006, 2007), trading volumes (Baker & Wurgler, 2006, 2007; Kumari & Mahakud, 2015; Liao *et al*., 2011), volatility (Baker & Wurgler, 2006), stock turnover rates (Asem *et al*., 2016; Baker & Wurgler, 2006, 2007; Chen *et al*., 2010; Chen *et al*., 2013; He *et al*., 2017; Huang *et al*., 2017; Kim & Byun, 2010; Kumari & Mahakud, 2015; Liao *et al*., 2011; Seok *et al*., 2019; Yang & Zhou, 2015, 2016; Zhou, 2018; Zhou & Yang, 2020) etc. The measures on the basis of the data for text analysis includes media sources for instance Facebook, LinkedIn, Google docs, Twitter, magazines, financial websites (like Reuters, Bloomberg) and journals (Audrino & Tetereva, 2019; Behrendt & Schmidt, 2018; Da *et al*., 2015; Johnman *et al*., 2018; Loughran & Mcdonald, 2016; Sun *et al*., 2016; Yao *et al*., 2017).

In behavioural finance, academicians extensively consider investor sentiments as a crucial cornerstone. Investor sentiments are divided into top-down and bottom-up approaches (Baker & Wurgler, 2007). The top-down approach is an investment strategy that begins with a broader assessment of macroeconomic factors and then narrows down to specific sectors, industries, and specific securities. In this approach, investors make focused investment decisions once the market and economy are assessed. The plan is to identify particular investment opportunities by first looking broadly at the variables that may impact different asset classes. However, the bottom-up approach is an investment strategy that focuses on analysing individual securities, like stocks or bonds, in contrast to beginning with a more comprehensive evaluation of macroeconomic variables. With this method, investors first assess individual companies and their core values, then make investment decisions. The rationale is to assess each tiny detail of each asset and make a portfolio based on the strength of each asset (Baker & Wurgler, 2007). This study uses a bottom-up approach in which first, specific securities are evaluated for how company-level factors contribute to investor sentiments and, consequently, stock returns.

The study of Qiang and Shu-e (2009) aims to assess the impact of sentiments on China's stock returns. The study reveals that investors' sentiments considerably impact the stock prices. In addition, the outcomes also show that the magnitude of positive news in sentiments is greater than the negative news. Moreover, Simões (2011) assesses the impact on the market reaction towards the change in dividend announcement and finds a positive impact on the European market. The sentiments are also examined during Ramadan, and researchers find their impact on stock prices (Białkowski *et al*., 2012).

Furthermore, Hu and Wang (2013) research on the Chinese market examines the relationship between noise trading and stock returns. They find that significant as well as small capitalization stocks are those which influence investor’s sentiments since such investors are incredibly speculative. The study on various sectors of the Istanbul Stock Exchange finds that variations in investor sentiments impact the conditional volatility of food, beverages, and banking sectors compared to retail and telecommunication sectors (Uygur & Taş, 2014). In addition to it, Li (2015) examines the impact of sentiments on the Chinese stock market and finds the utmost variation in stock price compared to other variables.

Stock returns and options are influenced not only by the investor sentiments of Taiwan, as quoted by the study of Szu and Yang (2015) during the financial crunch. Sun *et al*. (2016) also examined the financial crunch and found investor sentiments’ ability to forecast the returns of the S&P 500. Similarly, Renault (2017) researched the US market and found that after the period of high mood, there was a more profitable long-run anomaly than in the period of low mood. Therefore, in a bullish sentiment environment, investors must be more cautious in predicting stock returns as there is a conflict of interest among analysts in the Chinese market (Wu *et al*., 2018). In addition, the research of Audrino and Tetereva (2019) focuses on the dynamics of changing times and the impact of cross-industry news on Greek, Italian, German, and US stocks. The results show spillover impact and sentiments' significance in some sectors.

Lan *et al.* (2021) investigate the role of investor sentiments in seasoned equity offerings by Chinese companies. The research uses the stock market index and overnight stock returns as proxies for measuring the sentiments of investors, and the research shows that the sentiments potentially influence the pre-announced abnormal returns. The market corrects the sentiment-driven overvaluation of the market within a month. It suggests market timers exploit investors' sentiments to issue seasoned shares effectively. Reis and Pinho (2021) also emphasize their study on the constituents of S&P 350 and show the measures of investor sentiments in forecasting stock returns. It reveals how the irrationality in the behaviour of investors can predict stock returns. In China, the crash study finds that the rate of return increased by the same amount as the investor sentiments before the crash. After the crash, it increases slightly compared to the change in rate. It also finds that sentiments influence a stock's rate of return rather than the price of the stock. Therefore, retail investors are inclined towards herd behaviour in pessimistic periods rather than optimistic ones, yielding stock prices (Chen & Haga, 2021).

2.2.2.1 Share Mispricing and Stock Returns.

The definition of investor sentiments also covers the deviation bias between the price of an asset sustained by its fundamentals and its market price (Giglio & Kelly, 2018; Zhou, 2018), subject to be deemed mispricing. For instance, the average stock price set for analysis can be a fundamental asset price proxy. If this price varies from the theoretical price, then the difference is justified by sentiments. Therefore, stock prices become irrational, and Fama's efficient market hypothesis about well-informed markets does not hold. If we consider that there is no investor sentiment, then proxies only try to give a scale and, therefore, incorporate errors for sure. The sentiments have some kind of impact on the prices of assets, and due to this, any measure for sentiments efficiently captures the existing belief and its strength. In the same way, the crisis, market co-movements, crisis spillover, or contagions provide additional support for the interrelation of investor sentiments nature. In addition, crisis periods and financial market fluctuations are usually linked with increasing market co-movements (Reis & Pinho, 2021).

The empirical research uses dynamic conditional correlations between the daily stock returns of the US and ten emerging countries by reporting various spillover patterns of crisis in emerging countries (Hwang *et al.*, 2013). The results report that investor sentiments significantly and positively impact the analyst's expected biases after controlling the rational factors, for instance, underwriting relationships, reputation factors, and commission relationships. Sentiments strongly influence analysts' expected biases in conflict of interest, especially in commission relationships (Reis & Pinho, 2021). In addition, there is a relationship between optimistic bias and investor sentiments since analysts are not entirely rational and susceptible to existing market sentiments. When there are bullish market sentiments, the investors must be keen about their forecasts due to the conflict of interest (Wu *et al.*, 2018).

Many behavioural researchers argue about sentiments-based biases when there are persistent expectations. The studies (Brown & Cliff, 2004; Huang *et al.*, 2015) use sentiments to describe and forecast mispricing and focus on the high level of belief persistent following optimism or pessimism linked with long-term mispricing. In addition, behavioural finance evidence like overconfidence bias shows that irrational investors tend to resist updating their present beliefs to novel information, and this inclination is expected to contribute to forming persistent biased sentiments based on biased beliefs (Barberis & Thaler, 2003). The joined role of the effect of the sentiment on persistent expectations of investor’s bias and asset prices shows that extremely persistent sentiments are linked with prices of assets deviating from their fundamentals, thereby leading to long-run mispricing. On the other hand, the time of mean relapsing sentiments is linked with only short-run mispricing. This arbitrage is expected to be corrected so that further prices do not change (Han *et al*., 2022).

Another literature perspective, which disregards the value premium as a risk phenomenon, has a behavioural explanation. The explanation is that the value premium is a mispricing due to market irrationality and is not away from arbitrage because of limits to arbitrage (De Long *et al*., 1990; Miller, 1977). De Bondt and Thaler (1985) first enquired about this matter by lending the viewpoint of Basu (1977), who proposed that price-earning firms are undervalued since investors' reactions are pessimistic towards lousy news about these firms. However, the scholars could not find the root cause for mispricing; instead, they examined the overreaction of the market toward bad and good news, and such news led to overpricing and under-pricing.

Costless arbitrage and impossible mispricing from fundamentals in an idealistic economic state may exist. However, in the real world, there are limits to arbitrage as in the mania of dot-com, the intelligent investors keep on hedging funds into that bubble (Brunnermeier & Nagel, 2004) rather than rectifying it and the institutions purchase more supply of technology in comparison to individuals (Griffin *et al*., 2011). This evidence shows that it is tough to rectify the mispricing in reality (Zhou, 2018).

The empirical studies (Baker & Wurgler, 2006; Barberis & Thaler, 2003) have revealed that the proxies of investors' sentiment, such as trading volume anomalies or investor surveys, correlate with future stock returns. They also emphasize that mispricing driven by sentiments may lead to expected market patterns. However, most of the literature focuses on developed economies, and the study of Aggarwal (2022) explores the dynamics of sentiment in developing economies like the economy of Pakistan. Developing economies often show volatility and expected sentiment-driven mispricing because of inefficient information dissemination and lack of strict regulations. Regardless of the global literature, there is a lack of research on the impact of share mispricing on stock returns in Pakistan. Based on the above discussion, the following hypothesis is made:

H_1: *There is a positive impact of share mispricing (a proxy for market-based investor sentiment) on the stock returns in the Pakistani Stock Market*

2.2.2.2 Bond Yield Spread and Stock Returns.

The bond yield spread shows the investor's willingness to give money to a country in its capacity to borrow money and fund the deficits. This spread is meant to devise a feasible solution and make decisions for precise policies to solve the crisis. In this way, it is crucial to thoroughly understand the factors influencing investors' expectations and find sovereign yield spreads, particularly in the financial turmoil. The bond yield spread shows the premium the investors need to hold securities over safer assets. The noteworthy increase in yield spreads shows the non-consideration of financial markets in policy measures and bailout packages enough for the stability of an economy. In addition, the high level of spreads shows that the borrowing rate is economically unviable with demoralized economic development (Gómez-Puig *et al*., 2014).

The research of Spyrou (2013) undertook his study on the benchmarked government 10-year bond yields in Ireland, Spain, Portugal, Italy, and Greece by using it as a sentiment proxy in the University of Michigan Consumer Sentiment Index (MCSI) based on a survey conducted by the University of Michigan, the Economic Sentiment Indicator and Thomas Reuters. The results are statistically significant for investor sentiments regarding the bond yield spread of the country, particularly in the era of crisis, i.e., 2007-2011. Moreover, the studies of Aizenman *et al*. (2013) and Georgoutsos and Migiakis (2013) use monthly stock returns to reflect the allocation of portfolio effects between bonds and stocks in Ireland, Spain, Portugal, Italy, and Greece. The period of negative stock returns and financial turmoil go side by side with an increase in sovereign bond yield due to a rising tendency to hold a safer stock (Spyrou, 2013). Kim and Lee (2022) research established the statistical importance of the different factors linked to the market sentiment and then applied them to forecast the risk premium in the sovereign bonds of China. A composite sentiment index was created in the context of the study based on the indicators of investor risk appetite and market participation. The research findings have indicated that the sentiment factor and macroeconomic variables have outperformed the yield curve in predicting bond returns even during the financial crisis of 2008. It suggests its relevance in market turmoil due to a sentiment-driven "flight-to-quality" effect.

The sentiment generated by media can also affect bond yields and market returns. For assessment of this proposition, researchers demonstrate that the sentiment from newspaper articles can predict changes in the U.S. government bonds term structure, particularly in the short-term segment, due to higher volatility and the need to assess the actions of Federal Reserves. (Gotthelf & Uhl, 2019). This reliance on sentiment and news led to a new factor of the yield curve, the news sentiment, which is different from traditional yield curve factors and the macroeconomic variables. In their study, Piñeiro-Chousa *et al*. (2021) explain that social media's impact on stock market prediction has improved. However, the arena of the green bond market has remained unexplored. The green bonds are tied to sustainability initiatives linked with corporate responsibility and environmental concerns. The study used panel data analysis to examine how social investor sentiments can influence the green bond market. The study's findings can highlight social media as a source of valuable information for both equity and green bond markets.

Empirical evidence exists in the literature on the relationship between bond yield spread and stock returns (Baker & Wurgler, 2007; Smales, 2017). Behavioural finance theories also argue that investors are irrational and driven by sentiments (Barberis & Thaler, 2003). Emerging economies like Pakistan usually show more volatility and sensitivity to sentiments than emerged economies (Bekaert & Harvey, 1997). These studies suggest that the impact of bond yield spread on the stock returns is pronounced in emerging economies like Pakistan because of lower liquidity and market inefficiencies. More research is needed on the impact of bond yield spread on stock returns in Pakistan. Based on the above discussion, the following hypothesis is made:

H_2: *There is a negative impact of bond yield spread (a proxy for market-based investor sentiment) on the stock returns in the Pakistani stock market*

2.2.2.3 Gold Bullion and Stock Returns.

Gold is considered in this study as an investor sentiment proxy because it is among the preliminary types of money and is traditionally utilized as a hedge for inflation (Reis & Pinho, 2021). A hedge is an asset uncorrelated with another asset on average. Notably, a hedge does not curtail losses in turmoil or market stress as the asset may show a positive correlation in that period and a negative correlation in the standard period (Baur & Lucey, 2010). There are theoretical models explaining why gold is usually considered a haven. This feature is crucial in the globalization epoch since correlations are intensely augmented among other types of assets, and these constituents may significantly contribute to the role of gold (Baur & Lucey, 2010; Shabbir *et al*., 2020). A haven is an asset uncorrelated with the stock market in financial turmoil (Hood & Malik, 2013).

Raza *et al*. (2019) assess the asymmetric influence of oil prices, gold prices, and their related stock market volatilities of emerging economies. Using the non-linear autoregressive distributed lag model to assess the short-run and long-run asymmetries, the results show that gold prices impact the stock prices of large emerging economies and have an inverse impact on small emerging economies. The volatility of gold prices has an inverse impact on all the stock market's emerging economies in the short and long run. In this way, the emerging economies' stock returns are more susceptible to events and bad news in uncertain economic situations.

Afsal and Haque (2016) argue that the movements in the price of gold market are deemed to identify non-linear dependencies with the Saudi Arabian stock market. The study of Najaf and Najaf (2016) argues that because of financial crises all over the globe, developing and underdeveloped economies face low profits from their trade. The sentiment level in developing economies like Pakistan is low due to political instability. In this situation, the stock exchange in Pakistan has the worst selling, even though it has an inverse relation with the gold market. Basher and Sadorsky (2016) also confirm the volatility of oil and gold (commodities) with the stock prices. In the financial crisis, the relationship between gold and stock market volatility is inverse as in this era; gold is not realized as an efficient asset to be hedged (Choudhry *et al*., 2015). Generally, gold is deemed a haven against stock market risk in stable economic and financial conditions. The research confirms it studies that stock returns and commodities have a non-linear relationship due to their exceptional economic role. Gold is a highly liquid commodity and is highly encouraged by investors to assess alternate investments as a diversification tool during economic downturns (Bildirici & Turkmen, 2015; Tiwari *et al*., 2019).

The co-movement of oil prices and gold prices is becoming an increasingly researched topic in assessing the link between oil and gold, as the movements in their prices have significant implications for the financial markets of an economy. The rationale is that in inflationary economies, the investors hold the gold in an increasing trend owing to hedge against inflation (Naifar & Al Dohaiman, 2013; Reboredo, 2013). The study of Ciner *et al*. (2013) assessed the relationship among oil, stocks, gold, exchange rates, and bonds to provide evidence that these classes of assets are deemed as haven for each other. The results confirm that these commodities are haven against each other. Dyhrberg (2016) researches bitcoin as a virtual gold for hedging stocks and associates its trade with a future recession, offering low sentiment.

Nevertheless, the Harvard dictionary defines gold as an economic parameter for positive sentiments (Da *et al*., 2015). The investment in gold provides confidence to investors in times of turmoil and is considered an attractive and alternative investment due to the simplicity of the gold market. Gold is considered a portfolio diversifier since it is uncorrelated with other assets and generally lowers the portfolio risk. It is also notable that central banks maintain gold for diversification and protection of economic uncertainties (Ciner *et al*., 2013). Therefore, this study considers gold as a haven and hedge in the crisis era by the investors influencing sentiments by exploring the directional hypothesis of gold bullion.

Research reveals that gold price changes can predict the movement of the stock market, as Conover et al. (2009) argue that adding gold to a portfolio may significantly improve the performance of that portfolio since gold prices and stock returns are inversely related to the market turmoil. Emerging economies such as Pakistan are more sensitive and volatile towards investor sentiment changes compared to developed economies, and gold prices have a pronounced impact on stock returns. This unique dynamic of Pakistan's stock market is yet to be explored. Based on the above discussion, the following hypothesis is made:

H_3: *There is a negative impact of gold bullion (a proxy for market-based investor sentiment) on the stock returns in the Pakistani stock market*

2.2.2.4 Consumer Confidence Index and Stock Returns.

The consumer confidence indicator (CCI) indicates the future development of household savings and consumption. It is based on the answers regarding their expected financial situation and sentiment regarding the general economic situation, capability of savings, and unemployment (OECD, 2023). Several studies focus on the proxies for measuring survey-based investor's sentiments covering CCI (Kumari & Mahakud, 2015; Schmeling, 2009; Zouaoui *et al*., 2011). Even though consumer confidence and investor sentiments are dissimilar, a significant and positive relationship exists. Consumer confidence becomes a direct proxy for investors' sentiments in compliance with the American Association of Specific Investors from 1987 to 2000 (Zouaoui *et al*., 2011). After that, this metric is acknowledged for measuring investor sentiments. The relationship between the stock returns and CCI reveals no impact on the stock indices, as Bremmer

(2008) study shows. He studies commonly used indices like NASQAD, S&P 500, and Dow Jones.

Conversely, the study of Baker and Wurgler (2007) argues that local and global sentiments foresee relative and market returns for volatile growth and small portfolios. In addition, CCI as the investor sentiment proxy remains under consideration in Schmeling (2009) study. He studies the relationship between stock returns and investor sentiments for industrialized economies and finds a negative relationship. In addition, the inverse relationship holds for small, valuable, and growth stocks. In addition, the influence of CCI on stock returns is proportionally more substantial for less developed institutional markets and economies with the propensity of investor overreaction (Jansen & Nahuis, 2003; Lemmon & Portniaguina, 2006).

Yousuf and Makina (2022) explain the behavioural finance and adaptive market hypothesis paradigm, which is closely related to the rational expectations theory. The study was carried out on the Johannesburg Stock Exchange (JSE) and assessed the impact of behavioural risk factors on the efficiency of the market. The study determined by using quantile regression that the past market returns can significantly predict the future returns on JSE. The predictability can vary across different market conditions, and business confidence negatively affects the returns. In this regard, consumer confidence has a positive impact and indicates both behavioural and fundamental factors on investor behaviour.

The rational expectations theory assumes that the markets are efficient and that stock prices reflect all available information, including investors' sentiments. However, when the sentiment generates deviation from rationality, it can challenge the market efficiency and impact stock returns (Woo *et al*., 2020). Hence, the rational expectations theory provides a baseline for understanding economic decisions regarding investor decisions in the stock market. However, the research has illustrated that market behaviour is not purely rational, and factors like adaptability and sentiment have a significant role. It suggests the need for the integration of the elements of behavioural finance to gain a complete understanding of market dynamics.

Pakistan's market comprises a substantial proportion of individual investors, many of whom react to general economic news and political events, which are reflected in consumer confidence measures. Prior studies in emerging markets (including South Asia) have shown correlations between CCI and trading activity or stock returns, indicating its validity as a broad sentiment gauge (Lemmon & Portniaguina, 2006). The scholars (Lemmon & Portniaguina, 2006) further argued that consumer sentiment indices provide indirect yet powerful signals of market optimism and pessimism, particularly in economies with lower institutional investor activity. Based on the above discussion, the following hypothesis is made:

H_4: *There is a negative impact of consumer confidence index (a proxy for survey-based investor sentiment) on the stock returns in the Pakistani stock market*

2.2.2.5 Turnover and Stock Returns.

The turnover rate of stocks is the portion sold within a specific period. In the case of high investor sentiments, the investors actively participate in trades, resulting in high turnover and vice versa (Qiang & Shu-e, 2009). Turnover is the proxy variable for investor sentiment research (Baker & Stein, 2004; Baker & Wurgler, 2006). It shows the frequency of the sale and buying of stocks in the market at one point. Therefore, it shows the stock's liquidity. When investors' sentiments are high, there is a lead in the demand for transactions directed toward stocks with higher liquidity. Therefore, the activeness of the stock is coupled with the turnover rate (Chen & Haga, 2021). The researchers found that when the rate of turnover increases in the market, it usually owes to the domination of irrational investors, thereby causing an overvaluation in the market for a short period. This overvaluation shows that the rate of return in the future is low (Baker & Stein, 2004).

In comparison, when there is depression in investors, there is a vast reduction in their trading. The trading behaviour becomes conservative with fewer market transactions, thus leading to a low turnover rate. This variable shows the trading demand strength and is an indicator to assess investor sentiments (Chen & Haga, 2021). However, the research considers turnover as a liquidity measure related to investor sentiments (Ogunmuyiwa, 2010). It is argued that the turnover shows the varied opinions among investors at various times. A high turnover level shows investors' optimistic behaviour and vice versa (Baker & Wurgler, 2007). The optimistic and pessimistic behaviours influence the stock's liquidity. In financial literature, the trading volume or high liquidity of the market indicates stock overvaluation (Baker & Stein, 2004). In a market with limitations of short-sale, retail investors only take part in case of optimistic prospects, which increases the volume of trading. In this way, liquidity increases and directly relates to the optimistic behaviour of traders, which ultimately raises the demand for the overvalued stocks. From this perspective, the only investor is an optimistic investor with the limitations of short sales (Finter *et al*., 2012). Therefore, turnover is considered an irrational exuberance measure where liquidity shows investors' overreaction and, consequently, the stock's overvaluation (Baker & Wurgler, 2006).

In the Pakistani market, investment sentiments are influenced by herd behaviour prevailing in the stock market and directly impacting the stock returns (Javaira & Hassan, 2015). Stock prices and turnovers are declining due to economic and political instability, and investors are looking at each other and creating more herds to invest in during pessimistic periods (Arif *et al*., 2022). The investor sentiments theory shows the significant influence of the collective mood of investors on financial returns (Asem *et al*., 2016). It often diverges from the traditional and rational valuation methods in this regard, and the sentiments have been intricately linked with the stock turnover and affect the nature and frequency of trades (Liao *et al*., 2011). The research performed in markets like China and Korea substantiates the role of investor sentiments in shaping stock returns and the seasoned offerings of equity. It suggests that sentiment-driven behaviour can influence market inefficiencies (Ni *et al*., 2015). Chen *et al*. (2013) used the sentiment proxy of turnover ratio and applied the threshold model of the panel to eleven Asian countries. They find that worldwide optimism leads the industry's returns to be overvalued; however, it is undervalued in the case of pessimism. The studies of Yang and Zhou (2015, 2016) mentioned a sentiment index at the firm level based on the principal component analysis for the adjusted turnover rate, the logarithm of traded volume, the relative strength index, and the psychological line index. Market liquidity is reproduced from the turnover rate, which increases with investor sentiments (Kim & Byun, 2010). Based on the above discussion, the following hypothesis is made:

H_5: *There is a positive impact of turnover (a proxy for market-based investor sentiment) on the stock returns in the Pakistani stock market*

2.2.2.6 Advance-Decline Ratio and Stock Returns.

Though simple, the advance-decline ratio is a technical indicator in the implementation context. This ratio reveals the breadth of the market to assess the proportion of stocks that advance in a period to the proportion of stocks that decline in that period (P H & Rishad, 2020). The increasing trend of this indicator indicates that the market is going upward and vice versa (Brown & Cliff, 2004). It is an investor sentiment proxy (Brown & Cliff, 2004).

When the market sentiment is strong, investors' enthusiasm is relatively high, and often, the stock markets show an expected upswing. The meaning of this upswing is that the advance-decline ratio is high. On the other hand, in the case of down market sentiments, investors' enthusiasm is suppressed to some extent. An increasing number of the declining stock ultimately lowers the advance-decline ratio. However, the standard measure of the number of declining or increasing stocks does not cater to the volume of trade for the corresponding stocks (Jitmaneeroj, 2017; Kumari & Mahakud, 2015; Reis & Pinho, 2021).

The advance-decline ratio is also linked with investor sentiments in inefficient markets due to information asymmetry, resulting in excessive returns for investors and portfolio managers (P H & Rishad, 2020). The research of Zaremba *et al*. (2021) finds that herd behaviour and market breadth take the market downward or upward. Zaremba *et al*. (2021) analysed market breadth across 64 countries from 1973 to 2018 in their study. It has been found that the portfolios with higher market breadth consistently outperform the low market breadth. During this process, the accounting for the elements like momentum, size, and style have been considered accordingly (Joshi & Bhavsar, 2019). The pronunciation of the effect in the markets is limited regarding arbitrage opportunities and aligns with behavioural theories in collectivist societies.

Usually, the relationship between the advance-decline ratio (ADR) and stock prices is positive since the investors' sentiments maintain the market dynamics. Therefore, this ratio assists in realizing updated trends and can become a market performance indicator (Dash, 2016). However, some research studies find no significant relationship between stock indices and ADR (Joshi & Bhavsar, 2019). These studies also use lagged models, but the results argue that past ADR cannot forecast future market trends. In contrast, research indicates this ratio as a bearish and bullish market trend (Mohapatra, 2022). The study of Zakon and Pennypacker (1968) find that technical analysts use advanced-decline lines to predict short time space. They link the advance-decline ratio with investor sentiments, which results in additional market volatility.

The PSX often sees herd-driven behaviour, where retail investors follow trends across sectors. A high ADR indicates broad optimism, while a low ADR shows pervasive pessimism. Despite ADR's origin in technical analysis, its application as a sentiment indicator has been validated across both mature and emerging markets as a real-time reflection of trader psychology. Kumar and Lee (2006) highlight that in markets where noise traders are active, breadth indicators like ADR are useful proxies for herd behaviour. In emerging market studies, Chong and Lam (2017) observed that ADR can signal momentum-driven trading, especially where fundamentals are opaque or under-analysed. Based on the above discussion, the following hypothesis is made:

H_6: *There is a positive impact of advance-decline ratio (a proxy for market-based investor sentiment) on the stock returns in the Pakistani stock market*

2.2.2.7 Relative Strength Index and Stock Returns.

The relative strength index is a technical indicator that captures the magnitude of recent stock price changes. The high relative strength value suggests higher investor demand in the stock market and indicates bullish sentiment (Chong & Ng, 2008). This way, the size of current price changes is measured to assess whether the stock price is oversold or overbought. The relative strength index measures the swiftness and variations in price movements. It ranges between 0 and 100. J. Welles Wilder, the creator of the relative strength index (RSI), states that the market is overbought when the value of RSI is above 70 and oversold when its value is below 30 (Wilder, 1978). A positive relationship is expected between the relative strength and sentiment indexes. Chen *et al*. (2010), Hudson & Green (2015) and Yang & Zhou (2015) employ this variable to construct a composite investor sentiment index. The relative strength index is a primary tool used for technical analysis purposes, aligning with the investment sentiments and aligns with the momentum theory. It aids in assessing momentum, identifying overbought or oversold conditions, and significant reversal of the trends. Research affirms the relative strength index's effectiveness in predicting stock price directions, making it valuable for traders and investors (Baker & Wurgler, 2006; Reis & Pinho, 2021; Yang & Zhou, 2015, 2016; Zhou, 2018; Zhou & Yang, 2020).

Many studies emphasize the significance of one of the most adopted technical analysis measures, i.e., the relative strength index. These researchers find that the practice of commonly agreed methods in the markets may not benefit the market's investors. The price of shares in the stock market is that price, which can be estimated at any point by the market participants at the rule of demand and supply (Zhu *et al*., 2019). Rupande *et al*. (2019) evaluated the effectiveness of the relative strength index and moving average convergence/divergence technical indicators in predicting the stock price directions in the multiple global stock exchanges. Using standard parameters, it has been found that the moving average convergence/divergence made a correct prediction of the growing stocks, and the relative strength index achieved an 81% accuracy rate in 26 different stocks across different markets and indicated their suitability as the predictor of these risks. The study of Chen *et al*. (2010) suggests a measure of sentiment for emerging economies covering the application of principal component analysis of variables such as inter-bank offer rate, the volumes of short-selling, the money flow index, the relative strength index, turnover of the market, and the returns of Japanese and USA equity markets. The investors' quest to find stock prices requires analysing stock movements. The technical indicator used to estimate this movement in price is the closing price. The relative strength index measures the movement of stock prices over a specific time (Yang & Zhou, 2015). If a stock price is high, the resultant relative strength index also become high, thereby providing improved profits to the investors (Panigrahi, 2021).

Many retail investors in Pakistan rely on price-based cues (e.g., charts and RSI levels) due to limited access to in-depth financial analysis, making RSI a pragmatic indicator of behavioural shifts. The PSX exhibits momentum-driven trading patterns, aligning with the assumptions behind RSI, particularly under conditions of limited market depth and high volatility. Saeed & Sameer (2020), in a Pakistan-specific study, showed that RSI influences short-term trading behaviour due to high reliance on technical cues by local traders. Technical indicators such as RSI, although developed for trend analysis, are increasingly validated as behavioural proxies in markets dominated by non-institutional investors (Qadan & Aharon, 2019). Based on the above discussion, the following hypothesis is made:

H_7: *There is a positive impact of the relative strength index (a proxy for market-based investor sentiment) on the stock returns in the Pakistani stock market*

2.2.3 Firm-Specific Determinants of Stock Returns

2.2.3.1 Sales Growth and Stock Returns.

Sales growth is essential for assessing a company’s performance and affects revenue and profitability. Companies use it to measure the change in a company's revenue over a fixed period. The revenue comparison between two fixed periods shows whether the growth rate is positive or negative. It is one of the most influential metrics in a business used to measure the health of a sales team, and it is a critical indicator in determining and executing business strategy (Ajizah & Biduri, 2021). The study of Yulianto and Mayasari (2022) conducted a fundamental analysis of the companies by measuring sales growth and asset growth. They find that firms growing positively compete as well as position them in an appropriate way in the economy. Management avoids negative issues so that reputation is not harmed (Brush *et al*., 2000). Growth is also required to be managed and controlled as the company growing too fast is risky, and the human resource capability must be adjusted with control of constricted cost and rousingly busy operations. The stock returns are related to the increasing sales from one point to another time or from the growth of sales (Zai *et al*., 2021). The improvement in sales shows that prospects of future stock are also improved, and the investors look for issuers of shares. Investors consider sales growth to look at the expected profits (Nurwulandari, 2020). In this way, the company's growth impacts stock prices as it indicates good development and has positive feedback from investors. Companies with high growth rates have high levels of cash flows in the future and market capitalization, enabling them to have low capital costs (Magribi*et al*., 2023).

2.2.3.2 Financial Structure and Stock Returns.

The financing structure refers to the mix of debt and equity used to fund a firm's operations. A financing structure is considered optimal in maximizing the value of that firm(Pasha & Ramzan, 2019). The relationship between financing structure and stock returns can be positive or negative. The theoretical approach towards positive relations comes from the second proposition of Modigliani & Miller, which assesses the impact of capital structure on the systemic risk of stocks. It is found that stock returns increase with the increase in debt ratio (Pasha & Ramzan, 2019). Later on, this theoretical approach is empirically tested on the dataset of US firms, and the positive relationship between financing structure and stock returns is confirmed. The researchers found that the impact of change in leverage and stock returns is positive (Baker & Martin, 2011; Pasha & Ramzan, 2019).

On the other hand, empirical researches find a negative relation between leverage and stock returns for utilities, railroad, and industrial firms (Penman *et al*., 2007). The study of Adami *et al*. (2015) examines the relationship between financing structure and stock performance for the London Stock Exchange stock and finds the negative impact of debt financing on stock returns. The outcomes are elucidated by investors favouring investment in firms with financial flexibility and reap higher returns in low-leverages than high-leverage firms. The study of Penman *et al*. (2007) explains the relation behind unexpected results: the leverage figures have measurement errors, there are omitting risk factors that adversely impact leverage, and the market deviates price of leverage towards mispricing. The portfolio studies use debt ratio as a strategy for investment, which shows a positive relation between leverage and stock returns (Muradoğlu & Sivaprasad, 2012). They conclude that investment in portfolios with low leverage reaps high returns in a long time. That is why Modigliani and Miller's proposition does not hold. George and Hwang (2010) also find an inverse relation between financing structure and stock returns and explain that when risks other than leverage risk are present in the firm, and there is a high stock return for low-leveraged firms, there must be compensation for that risk. This is because firms have to make payments for debts, and investors do not show much interest in highly leveraged firms. This relation is also supported by various research studies (Acheampong *et al*., 2014; Henry Kimathi, 2015; Lee & Dalbor, 2013).

2.2.3.3 Firm Size and Stock Returns.

Although firm size is extensively utilized to predict stock returns, the explanation of the results on the size premium poses a challenge to asset pricing. The firm size is used as a factor of pricing, and it is a part of the asset pricing model owing to the assumption that the proxies of firm size have underlying characteristics or risks. Size is considered the best theory of expected returns. The capability of low market capitalization stocks or small stocks to exhibit size effect to generate high returns instead of stocks with high market capitalization stocks or large stocks is later empirically tested on different time spans at a wide market range (Astakhov *et al*., 2017). It is used in all pricing models empirically, which cover the three-factor Fama and French model (Karp & Van Vuuren, 2017), the four-factor Fama and French model, and the five-factor Fama and French model (Vakilifard *et al*., 2017). All these models cover an industry standard for assessing the expected rate of return on equity. In addition, firm size is one of the critical features that executives consider when assessing the investment appraisal discount rate (Graham & Harvey, 2001). Therefore, the size effect significantly impacts capital cost assessment in the financial practice.

Irrespective of the widespread recognition of size as a factor of pricing, it shows some puzzling characteristics that could be clearer to bring together, along with its ability to become a proxy for the underlying risk. In various empirical studies, the size premium (the difference between stock returns on small and stock returns on large stocks) is different over various regions (Cakici *et al*., 2016) and over time (Van Dijk, 2011). It is focused on January and small stocks, and if only a single percent of the smallest stocks are eliminated, the antagonistic relation between the firm's size and stock returns becomes positive (Moller & Zilca, 2008). In contrast to the idea that risky assets reap less returns in the era of economic turmoil, the size premium is focused on the period of the overall decline in the stock market (Hur *et al*., 2014). In addition, the rationale behind less risky or large stocks needs to be clarified, which has increased their capitalization. The stocks are considered risky as they have a positive stock price momentum (Astakhov *et al*., 2017).

2.2.4 Macro-Economic Determinants of Stock Returns

In order to make investment decisions, the economic factors affecting the stock market performance must be considered. The relation between macroeconomic variables and stock prices has been assessed considering that changes in macroeconomic variables impact the stock price by their impact on the expected cash flows and using the discounting rate. Numerous macroeconomic factors cause changes in the stock return. These factors cover inflation rate, industrial output, interest rate, money supply, and exchange rate (Neifar, 2023)

2.2.4.1 Inflation and Stock Returns.

Inflation is defined as increased prices of goods and services over time. Inflation is a critical economic concept that significantly impacts the economy and consumers. Inflation is measured using the Consumer Price Index (CPI), which can erode purchasing power, affect interest rates, and influence fixed-income recipients. In order to maintain economic stability, policymakers closely monitor inflation (Oner, 2023). When added to the other behavioural sentiments, inflation significantly affects investor sentiments and market dynamics, resulting in exaggerated market swings and suboptimal investment decisions (Reis & Pinho, 2021). Empirical research based on the Ross framework finds a negative relationship between inflation and stock returns, as an increase in inflation increases the nominal risk-free rate. It then increases the discount rate for the stock's valuation (Reis & Pinho, 2021; Schmeling, 2009; Tiwari *et al*., 2019). Inflation news decreases firm profits and impacts stock returns (Basarda *et al*., 2018; Saepuloh *et al*., 2019).

2.2.4.2 Interest Rate and Stock Returns.

The interest rate is the sum of interest due in a period being a part of lent, borrowed, or deposited money (named as principal amount). Interest rates play a significant role in determining the investment in stocks. It is considered to have a negative relation with stock returns using discounting or inflationary effect. Usually, when there is a rise in interest rate, then the securities of the money market, such as treasury bills, become more rewarding than capital market securities. This process reduces the stock demand and thereby reduces the stock market index. In this way, the interest rate is inverse to the stock market returns.

In contrast, some researchers provide empirical evidence of the direct relationship between interest rates and stock returns (Tetteh *et al*., 2019). A linear relationship exists between interest rates and share prices, negatively related to share price changes (Amarasinghe & Amarasinghe, 2015; Chirchir, 2014; Otieno *et al*., 2017).

2.2.4.3 Unemployment and Stock Returns.

Unemployment is the condition in which persons actively looking for suitable work cannot find it, and it is a crucial indicator of the health of the job market. The fluctuations in the unemployment rate occur due to various factors such as economic cycles, changes in the demanded job skills, and shifts in the labour market. The higher unemployment rate strains individuals' financial well-being, puts pressure on social safety nets, and becomes a significant policy matter for society and policymakers (RBA, n.d.).

The framing effect affects decision-making based on the presentation of information, and the unemployment rate significantly affects investors' sentiments. Positive framing boosts confidence and investment, while negative results in risk-averse behaviour. Also, fluctuations in the unemployment rate create economic uncertainty, influence investment decisions and market volatility, and highlight the importance of comprehending behavioural biases in finance (Dunham & Garcia, 2021).

In empirical research, there needs to be a clear consensus on the impact of unemployment on stock returns. The stock market analysts argue that stock prices rebound with increased unemployment announcements (Atanasov, 2021). The scholar finds that the announcement of increasing inflation is good news for firms during economic expansion and bad news during the contracting economy. The expected unemployment rate influences the growth rate of the money supply, which consequently impacts the stock market's returns (Atanasov, 2021; Gonzalo & Taamouti, 2012). Another possibility is that with an increase in unemployment, the monetary policy is revised by decreasing the interest rate. It consequently increases the stock market price (Gonzalo & Taamouti, 2017).

On the other hand, an inverse relation exists between unemployment and stock returns. The rate of less unemployment reveals a healthy economic state, thereby leading to increased consumer spending and a high level of firm profits, which can positively impact stock prices (Algieri *et al*., 2020).

2.2.5 Stock Return Volatility

Volatility refers to unexpected change in the asset prices and is considered one of the most significant characteristics of the financial markets. It is directly linked to market uncertainty and has a profound impact on the investment decisions of individuals and firms. The volatility shows the uncertainty about an asset's future price and is usually measured using statistical tools such as standard deviation or variance.

Various factors contribute to stock market volatility. One of the primary influences is monetary policy. Under an expansionary (loose) monetary policy, stock indices tend to rise due to increased liquidity and lower interest rates. Conversely, a contractionary (tight) monetary policy is usually associated with declining stock prices. Changes in interest rates, particularly the liberalization of interest rates, also affect the risk-free rate and, consequently, the cost of capital. As interest rates rise, the risk-free rate tends to increase, raising the overall cost of investment and impacting firms' expected returns. These dynamics are crucial to understanding investor expectations, especially during dividend announcements or in anticipation of higher market returns (Bhowmik & Wang, 2020).

The relation between the stock return and its volatility, often used as a proxy of the risk, has been a significant topic in financial research. The theoretical asset pricing models typically link the stock return and its variance or co-variance between its return and market portfolio return. However, there is controversy on the positive or negative relationship. Most asset pricing models propose a positive relation between the stock return and its volatility. In contrast, the traditional financial models suggest a negative correlation between stock returns and stock volatility. Several studies empirically test the relationship between stock returns and stock volatility; however, the findings are mixed (Hussain *et al*., 2019; Varughese & Mathew, 2017). Empirical research needs to utilize datasets efficiently; however, the ARCH and GARCH models are frequently utilized to consider the time-changing behaviour in the stock return volatility. The results show a significant positive or insignificant relation between the conditional variance and expected returns (Kashyap, 2023). Even studies report significant positive relations, making the empirical findings inconclusive (Ghorbel & Attafi, 2014). Studies have also noted that volatility shocks can persist over extended periods, amplifying their impact on stock prices and potentially distorting market efficiency (Li *et al*., 2005). This persistence implies that market reactions to volatility are not merely short-term phenomena but may have long-lasting effects on return dynamics. Based on the above discussion, the following hypothesis is made:

H_8: *The stock return volatility negatively impacts stock returns of the Pakistani stock market*

2.2.6 Lead-Lag Relationship

Lead lag is the relationship between two variables in which one variable leads and initiates change in the other variable. It is typically used in assessing cause-and-effect relationships or forecasting expected outcomes. The bandwagon effect is generally a psychological, phenomenal impact from other people with fads, ideas, thinking behaviour, and beliefs based on the trends. When more and more people start thinking similarly, investors hope for the bandwagon. Investor sentiments help investors better understand stock returns over time. The investor sentiments in this situation flow with the trending market stocks and earn maximum stock returns (Hu *et al*., 2019). Investors follow the prevailing market trend, even if other factors may not support it (Hu *et al*., 2019). This effect makes finding the causality between investor sentiments and stock returns challenging. The influential work of researchers shows that the bandwagon effect reduces the expectations of stock returns (Brown & Cliff, 2004). At a certain point in time, the high sentiments of investors increase stock prices and stock returns. It shows a positive association with investor sentiment and stock return at the same point in time.

In the context of Pakistan, the study of Khan and Ahmad (2018) explores lead-lag and the bi-directional relationship between market returns and investor sentiments and finds the irrationality of investors in dragging the market away from sustainability and the fundamentals of the economy. The noise traders behave irrationally by following trends and news, as investigated in the study on the Pakistan Stock Exchange market capitalization (PSX) (Raza *et al*., 2019). Such behavioural biases impact asset pricing, as discussed in the study of Rashid *et al*. (2019), on the equity market of Pakistan. They argue that momentum factors and investor sentiments enhance the chances of mispricing. Moreover, Tauseef (2020) researches the causality between sentiments and stock returns for Islamic and conventional stocks in Pakistan. The researcher finds that trading actions caused by investor sentiments persist for a month. However, when such stock prices rise, this movement reverses in two months. Terrorist activities also impact the mood of investors. Other than economic loss, the terrorist activities create a hype of uncertainty in the Pakistani market, and the investors overreact to such activities, which later on recover the market trend (Ali *et al*., 2020). On the other hand, sentiments can play a significant part in the economic and business activities from the perspective of the Pakistani stock market (Muhammad, 2022). Based on the above discussion, the following hypothesis is made:

H_9: *The investor sentiments have lead-lag and causal relation with stock returns of the Pakistani stock market*

2.3 Schematic Diagram of Conceptual Framework

Figure 2.1

Conceptual Framework Diagram

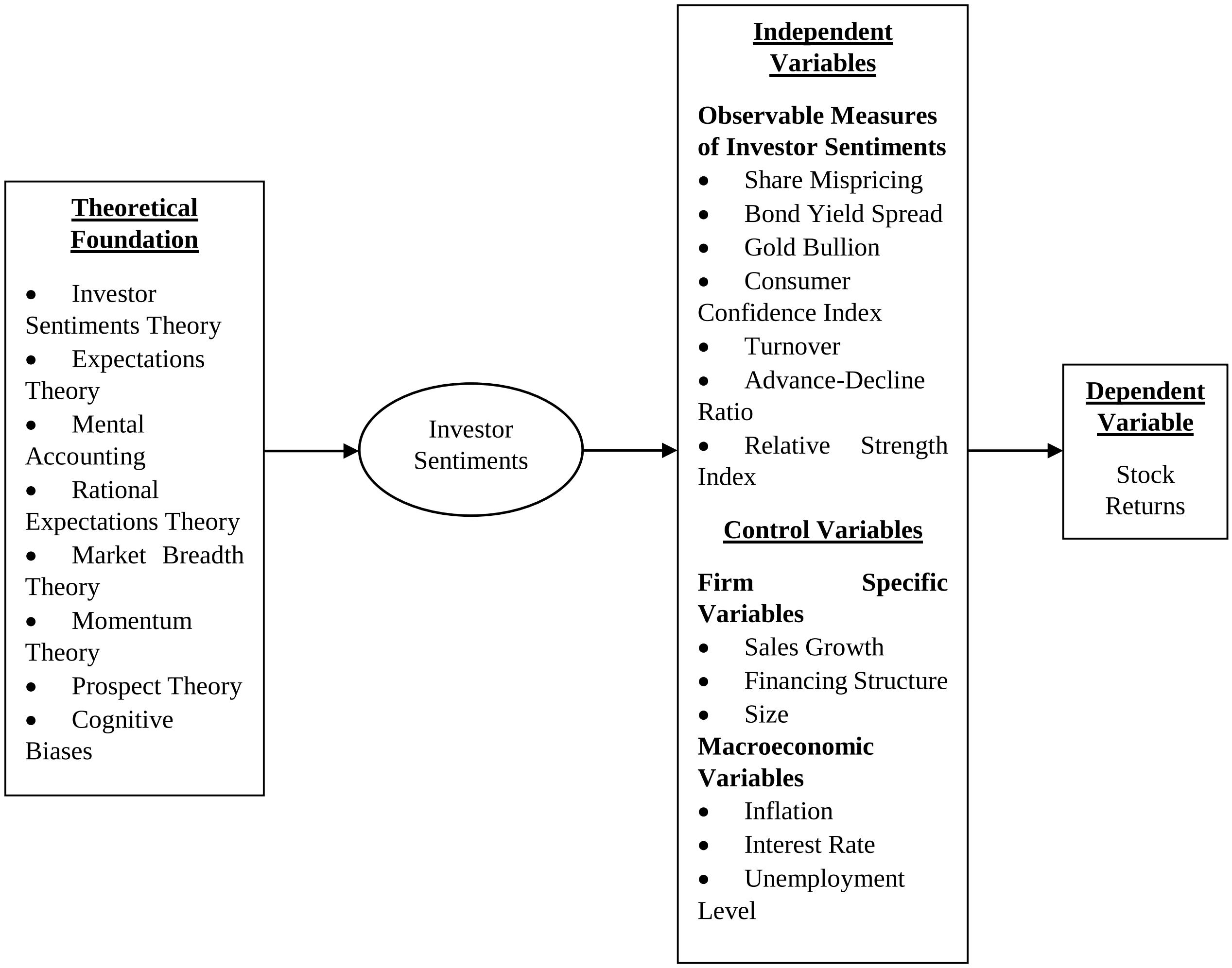

Figure 2.1 illustrates the schematic diagram of the theoretical framework. Where stock returns are the dependent variable, whereas investor sentiment is the independent latent variable measured using proxies, i.e., share mispricing, bond yield spread, gold bullion, consumer confidence index, turnover, advance-decline ratio, and relative strength index. Moreover, the firm-specific control variables are sales growth, financing structure, and size. Furthermore, inflation, interest rate, and unemployment are the macroeconomic control variables.

Both inflation and interest rates represent fundamental macroeconomic factors that exert distinct yet complementary influences on stock market behavior and investor sentiment. The inflation rate, measured by the Consumer Price Index (CPI) growth, captures the general rise in price levels in the economy, affecting purchasing power, cost structures, and ultimately firm profitability. Inflation fluctuations can shape investor expectations about future economic conditions and corporate earnings, thereby influencing stock returns. On the other hand, the interest rate, proxied by the Karachi Interbank Offered Rate (KIBOR), reflects the cost of borrowing in the financial system, impacting corporate financing decisions, investment activity, and the opportunity cost of capital. Interest rate movements directly affect discount rates used in asset pricing models and influence liquidity conditions in the market. Including both variables allows the model to account for different channels of macroeconomic influence on stock returns and investor sentiment, providing a more comprehensive control framework. Additionally, both variables are widely available on a quarterly basis from official sources, ensuring consistent data frequency aligned with the study period and facilitating robust empirical analysis. Therefore, their combined use enriches the explanatory power of the model by capturing diverse economic dynamics that jointly affect equity market performance. Interest Rate and Inflation are the commonly used variables in different studies on stock returns; therefore both of the variables are included in the initial. However, the diagnostic tests are performed before running the final model and only those variables are included in the final model which fulfil the necessary criteria.

In short, this chapter is divided into four parts: The first part is about the theoretical framework of the study, the second part is about the empirical review of the study, the third part is about the schematic diagram of the theoretical framework, and the fourth part is about the research gap of the study. The theoretical framework portion covers numerous theories related to the study, i.e., random walk theory, risk-return theory, investor sentiment theory, expectations theory, mental accounting, rational expectations theory, market breadth theory, prospect theory, and some biases such as overconfidence bias, loss aversion, herd behaviour, framing effect, anchoring bias, and recency bias. The empirical review covers numerous studies supporting the relationship between investor sentiments and stock returns. Based on the theoretical and empirical underpinning, this chapter further frames the schematic diagram and gap of the study.

2.4 Research Gap

Past studies have introduced multiple sentiment measures, exploring non-observable (latent) variable characteristics. These measures can be divided into three categories: those based on market data analysis (including aspects like trading volume, volatility, closed-end mutual funds, dividend premiums, stock turnover rate, and number of IPOs, among others); those founded on surveys and investigations; and sentiment measures based on the occurrence of specific keywords within media data sources like Twitter, Facebook, Google docs, LinkedIn, newspapers and magazines, and financial websites (Bloomberg, Reuters). Understanding how investor psychology influences stock market returns is crucial for a deeper comprehension of markets and the predictive capacity of investor sentiment. Over 34 sentiment proxies have been identified within market data (Baker & Wurgler, 2006; Reis & Pinho, 2021; Seok *et al*., 2019; Zhou, 2018). While indexes have been created using these measures, no agreement exists on the optimal individual proxies or indexes. Various sentiment proxies show different effects on returns or variance; this study thus re-examines the matter of selecting individual proxies over indexes. The study does not use a composite sentiment index, the proxies employed are methodologically novel and theoretically justified, particularly in the context of the PSX where sentiment indicators remain under-explored.

The study of Aggarwal (2022) critically reviews 81 scholarly articles to assess market sentiment measurements and their implications for stock market behaviour. Despite extensive research, the literature needs a more precise definition of sentiment, resulting in conflicting results across different sentiment proxies. Aggarwal (2022) suggests a re-evaluation of sentiment from a psychological perspective, needing further examination across diverse investor types. Developing effective sentiment proxies could benefit investors and aid in policy formulation, given the predictive power of investor sentiment on stock returns. This study focuses on individual sentiment measures instead of joint index, utilizing survey and market data based on frameworks proposed by Qiu & Welch, (2004), Kearney and Liu (2014), and Reis & Pinho (2021). Specifically, this research introduces three unique proxies: share mispricing, bond yield spread, and gold bullion price; as representations of investor sentiment, each with distinct explanatory power.

Conventional finance assumes no deviation of security prices from fundamental values due to arbitrageurs' ability to equilibrium. However, empirical researches (Chang *et al*., 2007; Han *et al*., 2022; Zhou & Yang, 2020) increasingly support evidence of pricing anomalies. This raises questions about why arbitrageurs fail to capitalize on mispricing opportunities (Doukas *et al*., 2010). Arbitrage risk plays a significant role in causing price deviations from fundamentals, exemplified by share mispricing, where market prices diverge from intrinsic values (Giglio & Kelly, 2018; G. Zhou, 2018). In comparison to the American Association of Individual Investors (AAII) sentiment survey which directly captures the expectations of investors, but they may suffer from response bias; share mispricing is derived from fundamental valuation model of share price deviation of market value from intrinsic value. This valuation model shows real market behaviour instead of self-reported expectations. Moreover, market indices like Volatility Index (VIX) measure implied volatility; however share mispricing identifies valuation anomalies that persist beyond short-term volatility changes. Also the sentiments from financial news such as from Reuters, Bloomberg, etc. reflect existing narratives, whereas share mispricing provides a valuation-driven quantitative indicator of sentiment. Therefore, this study introduces a new proxy for measuring share mispricing in Pakistan, illustrating how excessive optimism in bullish markets leads to overvaluation and excessive pessimism in bearish markets leads to undervaluation in comparison to existing measures of investor sentiments. Share mispricing is computed as the difference between the market price and the intrinsic value, where the intrinsic value is calculated using the Benjamin Graham formula. This formula integrates earnings per share (EPS), book value, and other financial fundamentals to offer a comprehensive and objective measure of a stock's valuation. Notably, the Graham-based intrinsic value proxy has not been used previously in Pakistani capital market studies, making it both novel and contextually relevant.

Bond yield spread, a key financial indicator for assessing economic fundamentals, is influenced by non-fundamental factors like investor risk aversion and market imperfections (Favero & Missale, 2012; Geyer *et al*., 2004). The behavioural finance perspective of bounded rationality explores how these factors impact asset prices over time. Researchers (Baker *et al*., 1977; Baker & Wurgler, 2006, 2007; Schmeling, 2009) document equity market inefficiencies and the rationale behind extreme movements in bond spreads. The study of Eichengreen and Mody (1998) finds that variations in fundamental variables only partially explain sovereign bond spread changes, prompting a re-evaluation of underlying forces. Advocates of behavioural finance seek to link bond yield spread with market sentiment (Schmeling, 2009). Menkhoff and Rebitzky (2008) propose an indirect measure of investor sentiment through bond yield spread, highlighting its close relationship with sentiment rather than economic fundamentals (Kumar *et al*., 2018; Kumar & Lee, 2006). The variation between the ten-year bond yield rate and the three-month bond yield signals shifts in sentiment, influencing investor equity exposure adjustments to capitalize on sentiment-driven stock return impacts. Existing sentiment indices based on survey measures such as University of Michigan Consumer Sentiment measure investor's expectations about economic conditions, which is subject to biasness and subjective judgment; however bond yield spread is an objective economic indicator signaling recession fears or economic optimism. In comparison to market-based measures such as VIX or S&P are stock market indices, whereas bond yield spread in a long-term indicator of risk sentiment, which reflects the expectation of investors about economic growth and future interest rates. Media-based sentiment analysis reflects narratives about market risks; whereas bond yield spread provides a quantifiable, real-time market consensus on future economic conditions, avoiding the limitation of sentiment biases in news reporting. Therefore, this study pioneers using bond yield spread as a sentiment proxy in Pakistan, emphasizing its role in reflecting investor confidence in future economic growth or signaling market disruptions like inverted yield curves in comparison to existing measures of investor sentiments (Reis & Pinho, 2020).

Gold, a historical value storage and medium of exchange, traditionally serves as an inflation hedge and offers portfolio diversification benefits (McCown & Zimmerman, 2006; Sherman, 1982) and protection for investors against exchange rates (Capie *et al*., 2005). Empirical research and financial media highlight gold's significance as a haven during market crashes (Baur & Lucey, 2010; Baur & McDermott, 2010). In the modern era, developing novel investment tools such as exchange-traded funds (ETFs) has caused gold market participation among retail and institutional investors. Conover *et al*. (2009) recommend that investors significantly improve portfolio performance after adding considerable exposure to the equities of precious metals firms. However, Riley (2010) reveals the advantages of precious metals, such as strong negative association and good expected return with other classes of assets. Hammoudeh *et al*. (2011) focused on the significance of other precious metals other than gold in the management of risk. Given the increasing relevance of precious metals, Hood & Malik (2013) use gold as a potential haven or hedge. Gold is adopted as a safe asset in this study in case of low sentiments. Gold is used as a hedge and a haven for major stock markets and is a restoring force for the financial system by registering losses before extreme adverse market shocks (Baur & McDermott, 2010). This study also uses gold as a hedge and a haven for the Pakistani stock market as an investor sentiment proxy. In comparison to subjective surveys, the demand of gold is driven by expected inflation and risk aversion attitude of investors, providing a real-asset sentiment proxy. VIX as market-based measure of sentiment is one of complementing indices to measure risk sentiment of investors; whereas gold prices move inversely with stock indices. Moreover, sentiments extracted from news about geopolitical risks or inflation correlated with gold prices, but actual holdings of gold and trading volumes provide stronger behavioural evidence. Therefore, this study innovatively uses gold as a sentiment proxy in the Pakistani stock market, emphasizing its role during periods of low sentiment and as a safeguard against market volatility curves in comparison to existing measures of investor sentiments.

This study investigates the lead-lag relationship between returns and sentiment proxies, deviating from traditional index-based approaches. Moreover, it addresses the lack of panel data studies in Pakistan, which predominantly rely on time-series and cross-sectional modeling (Ali *et al*., 2020; F. Hussain & Mahmood, 2017; Raza *et al*., 2019; Shabbir *et al*., 2020) and cross-sectional data modelling (Abideen *et al*., 2023; Ahmad & Wu, 2022; Arif *et al*., 2022; Din *et al*., 2021; Javaira & Hassan, 2015; I. Khan *et al*., 2021; Parveen *et al*., 2020; Rasool & Ullah, 2020; Rehan *et al*., 2021; Shafqat & Malik, 2021; Shah & Malik, 2021). Only a few studies, such as Sarwar & Hussan (2013), study the impact of investor sentiments on stock returns using market premium, size, a book-to-market ratio, leverage, dividend yield, cash flow-to-price ratio, earning-to-price ratio, uncertainty, discretionary accrual, and trading volume as measures of investor sentiments. Another study (Khan & Ahmad, 2018) found the related topic of the bi-directional and lead-lag relationship of investor sentiments on the stock returns of Pakistan, where sentiments are measured using survey data and stock returns are measured from panel data of PSX firms. The third study (Khan *et al*., 2023) found on the related topic is very recent on the impact of the relationship between investor sentiments and stock returns in Pakistan, where sentiments are measured using price-earnings ratio, share turnover, and money flow index. This study pioneers the use of panel data to measure sentiment proxies (share mispricing, bond yield spread, gold bullion, consumer confidence index, turnover, advance-decline ratio, and relative strength index) in Pakistan's developing economy for the first time, contributing to a deeper understanding of sentiment dynamics in the market. While the study does not develop a composite sentiment index due to data limitations and market-specific characteristics, the proxies used are theoretically rich, empirically valid, and collectively offer a robust representation of investor sentiment. The multidimensional approach to measuring sentiment enhances the explanatory depth of the model and contributes to literature on emerging markets where formal sentiment indices are largely unavailable. Therefore, the differentiation in proxy selection is not merely a substitution but a deliberate methodological innovation rooted in behavioural finance theory and tailored to the structure of the local market.

CHAPTER 3

RESEARCH DESIGN AND METHODOLOGY

The research design and methodology is an essential section of a thesis, which outlines the approach and plan used to assess the research questions underlined in the introduction chapter. This chapter provides a detailed overview of the methodological aspects of the role of investor's sentiments on the stock returns of Pakistan Stock Exchange-listed firms. The quality and strength of research are based on the methodological strength in the context of planning, data collection, data analysis, and reporting of facts. A research design plays the role of a planner in the project. In this way, confidence is placed on the results drawn from a study. A research design is crucial to assist the smooth functioning of different research operations. In this way, the research process is made as efficient as possible to extract the maximum amount of information from a minimum amount of money, effort, and time.

3.1 Research Philosophy

The research philosophy is a belief in the methodology regarding the collection of data, analysis of data, and interpretation of data to give meaningful implications (Holden & Lynch, 2004). Choosing the right philosophy in the research methodology is crucial as this choice makes knowledge meaningful and extensive. The research philosophies are of four kinds: ontology, epistemology, axiology, and methods (Saunders *et al*., 2019); which are discussed in the context of research paradigms.

The research paradigms are the ways of assessing social happenings from which a specific understanding can be taken, and explanations are made (Bell *et al*., 2022). The research paradigms have four stances: positivism, realism, interpretivism, and pragmatism. These paradigms represent different ontological, epistemological, axiological, and methodological perspectives determining the researcher's view of scientific methods (positivism), reality (realism), knowledge (interpretivism), and nature of inquiry (pragmatism). This study follows the positivism research paradigm discussed in the light of research philosophies (ontology, epistemology, axiology, and methods) (Saunders *et al*., 2019):

Positivism forms causal relations, focusing on measurable as well as observable occurrences (Gujarati & Porter, 2022). The situation of financial markets is actual, and the interpretations are made and estimated scientifically. Therefore, this study uses the positivist philosophy. This study follows a positivist philosophical stance rooted in the opinion that the study of the social world can be made by empirical and objective means (Bell *et al*., 2022). In the perspective of this study, a positivist stance is also considered suitable for assessing the quantitative relation between investor sentiments and stock returns in the PSX-listed firms.

Ontology is another research philosophy related to the nature of reality for producing precise knowledge (Saunders *et al*., 2019). There are two aspects of ontology exist objectivism and subjectivism (Bell *et al*., 2022). The concept of objectivism shows the position of social objects in the real world other than social actors related to their existence. On the other hand, subjectivism shows the creation of social phenomena as a result of actions done by social actors related to their presence (Saunders *et al*., 2019). The ontological perspective of this study relates to positivism, in which the presence of objective reality is realized to study and understand it (Bell *et al*., 2022). Following an objective positivist stance, this study examines investor sentiments and stock returns as quantifiable phenomena without individual perceptions.

Epistemology is related to the adequate information in the concerned field. The researchers epitomize objects as accurate, and it is hard to attach feelings to the data (Bell *et al*., 2022). In the epistemological stance, the positivism principle uses the natural scientist approach as it works with an evident reality of society, and the results have generalizations like implementing a law. This study's epistemological viewpoint is objectivist derived from positivism, confirming that knowledge derivation is made from observable and objective facts (Saunders *et al*., 2019). The working of financial markets is a social phenomenon, and the inferences are not subjective to the social actors. Therefore, this study uses objectivism philosophy. The goal of the relation between investor sentiments and stock returns is to reveal the patterns and general laws leading to the relationship between investor sentiments and stock returns, thereby contributing to the growing knowledge of finance.

Axiology is related to the study of value judgment, which covers ethics (Saunders *et al*., 2019). Throughout this study, the researcher maintains impartiality to lessen the chances of subjective interpretations and personal biases. The data collection process is systematic and adheres to the set protocols to ensure the replicability and reliability of the research outcomes (Bell *et al*., 2022).

In the methods, the quantitative research design uses statistical methods to assess the data of historical stock prices. Furthermore, the quantitative research design assesses the correlation between investor sentiments and stock returns. This study aims to generalize generalized outcomes to the comprehensive population of listed firms in PSX. In this way, the research design provides empirical support to investor sentiments that impact stock returns.

3.2 Research Approach

The research approaches provide a leading pathway to follow the research process. These approaches must be related to research philosophies since research is a systematic process. There are two types of research approaches: induction and deduction. The induction approach is a theory-building bottom-up research approach that starts with observing a problem. The data is collected and analysed to solve that problem, and the solution is proposed. This proposed solution becomes a theory and is related to interpretivism. However, the deduction is a theory-testing top-down research approach with a prevailing theory. The theory is tested using a hypothesis; then, the data is collected and analysed to solve the acceptance or rejection of the hypothesis (theory). This approach is related to positivism's philosophical stance (Saunders *et al*., 2019).

This study uses a deductive approach coupled with a positivist philosophical stance to test established theories with the help of hypotheses, as explained in Chapter 2. The research hypotheses explore the causal relation between variables, particularly investor sentiments and stock returns. The research is firmly grounded in the theoretical framework of existing theories about sentiment analysis, investor behaviour, and stock market dynamics. This reliance on existing theories provides a strong foundation for the research.

The research is based on literature that discusses the role of investor sentiments in impacting stock returns in developing and developed economies. The quantitative research design is used to systematically gather and assess numerical data by collecting historical stock return data and proxies of investor sentiments to assess and quantify investor sentiments. Statistical methods, such as regression analysis and other diagnostic tests, are used to test the relations established in the theoretical framework. Based on the results, the hypotheses are either accepted or rejected and interpreted in the context of prevailing literature and theories. The procedure of this study limits bias and improves reliability, thereby allowing for interpretations of the established relations.

3.3 Research Design

The research design provides a roadmap for further plans of action in the research. There are three types of research designs: exploratory, descriptive, and explanatory research design (Saunders *et al*., 2019). The exploratory research design studies meaningful results to discover new happenings and examine the process from a new perspective. The descriptive research design is a study that exposes an accurate picture of gathered data prior to the data analysis (Bougie & Sekaran, 2019). The explanatory research design studies a problem explaining the relationship between variables, typically between dependent and independent variables (Saunders *et al*., 2019).

The positivist philosophical paradigm and deductive research approach are usually coupled with an explanatory research design. This study also uses an explanatory research design since it describes the causal (strength and direction) relation between investor sentiments and stock returns.

3.4 Research Strategy

The research strategies are plan of action to solve the research problem systematically (Bougie & Sekaran, 2019). This study uses an archival research strategy since it retrieves data from the past (i.e., from 2012 to 2019) in answering the research questions. Archival research is based on the historical data by archiving the historical documents and record (Saunders *et al*., 2019). It consists of the examination of the prevailing records, datasets, and documents to answer the research queries and examine the particular topic. This strategy uses secondary rather than primary data by examining the historical pattern of investor sentiments and stock returns in PSX-listed firms. The data sources include financial reports, market data, news archives, and macroeconomic data for firms' quarterly intervals. Data quality is verified for the accuracy and reliability of archival data sources.

3.5 Time Horizons

The time horizon covers the research based on the number of participants and the period involved. There are three types of studies concerning time: cross-sectional, time series (longitudinal), and panel data study. The cross-sectional study studies more than one cross-section at a specific time. The time series study studies a specific cross-section at more than one point in time. However, the panel study studies more than one cross-section at multiple points (Saunders *et al*., 2019). This study uses panel data to study the impact of investor sentiments on the stock returns of Pakistani listed firms over time (i.e., 2012-2019).

3.6 Sampling Technique

This study uses a purposive non-probability sampling technique since the non-financial companies listed in PSX are selected. Further, it excludes financials and utilities based on the fact that these companies have different natures of business, obligations, requirements, and reporting methods, so a set of companies (non-financial) are selected in this research in order to gather similar types of firms with the same features to maintain the accuracy and reliability of results. This exclusion is intentional, as financial institutions and utilities differ significantly in terms of business structure, financial reporting standards, regulatory frameworks, and risk-return profiles. Including them compromise the comparability and reliability of the results. Non-financial firms offer standardized financial reporting, which is critical for accurately applying models such as share mispricing and sentiment proxies. This aligns with the methodological need for consistent data across multiple years. The firms are chosen from the KSE-100 index to ensure the representation of samples from different market conditions and industries. It helps ensure that outcomes are not confined to a particular sector. This ensures that the sample captures a broad cross-section of market conditions while still maintaining data quality and relevance. Since this study explores the impact of investor sentiment on stock returns, it is essential to select firms that operate under similar market conditions and investor behavior dynamics. Non-financial firms tend to have more uniform investor bases, making them more suitable for sentiment analysis. In purposive sampling, the focus is not on attaining statistical representativeness but on the sample size practicality to ensure the sufficiency of the sample in providing meaningful patterns and insights (Saunders *et al*., 2019).

3.7 Population

In the field of research, all items cover a population. Research covering a complete list of all population items becomes a census. In this way, all items become part of the sample, and there is no chance of missing elements with utmost accuracy. However, there are more practical approaches to follow. Therefore, the selection of sample size is crucial and depends on the population of the study (Kothari, 2017). This study population comprises the firms listed in the stock exchange, i.e., the Pakistan Stock Exchange (PSX).

3.8 Sample Design

Sample design is a predefined plan for attaining a sample from the population. It is the process of selecting items from the population for a sample. The sample design covers the item numbers that become part of the sample, thereby determining sample size. This is a pre-step of data collection. Therefore, the determination of sample size from the sample design is crucial. The appropriate sample design can give precision and ease to the researcher (Gujarati & Porter, 2022). First, the sampling unit is selected, i.e., an individual, a company, a firm, a university, etc. A study can cover one or more than one sampling unit (Kothari, 2017). This study uses a single sampling unit, i.e., firms, to assess the impact of investor sentiments on stock returns. The next step is to select a sampling frame, i.e., a list of sources from which the sample is extracted. The sampling frame must be representative of the population. This study uses Pakistani-listed firms as a sampling frame. After selecting the sampling frame, the sample size is determined with an optimum selection from the population having traits of representation, adeptness, and reliability. The determination of sample size depends on the population variance, the estimated confidence level, parameters of interest, and budgetary constraints to decide the sample size. The parameter of interest for the population must have some common traits (Gujarati & Porter, 2022). This study uses the non-financial listed firms of the PSX as the parameter of interest in the population following the literature studies (Ma *et al*., 2023; Sarwar & Hussan, 2013; Simpson, 2013) .

3.9 Data Collection Techniques

In management and business research studies, two standings are used to set apart data collection and analysis techniques, i.e., quantitative and qualitative procedures (Bell *et al*., 2022). The name depicts the difference between the two techniques: the first focuses on numeric data (scale), and the latter focuses on non-numerical data (numbers). The quantitative technique is mainly used for data collection, generating or using numerical data such as questionnaires or secondary data. On the other hand, the qualitative technique is mainly used for data collection, which categorizes or uses non-numerical data. Concisely, data that uses words is quantitative, and data that uses pictures and videos is qualitative. The research methods use either one data collection technique and data analysis procedure (mono method) or more than one data collection technique and data analysis procedure (mixed method) (Saunders *et al*., 2021). There is a particular relation between the chosen techniques of data collection and the results. The outcomes are influenced by the techniques chosen. The point of concern is that there is no possibility to find out the type of such influence. All different procedures and techniques have dissimilar outcomes, and it is possible to use various methods to rule out the method's impact. It can enhance the confidence level of the results obtained (Kothari, 2017). This study uses quantitative and mono-method data collection techniques and data analysis procedures, as the data is based on the numerical dataset.

3.10 Data Collection Methods

Data collection initiates once a research problem has been identified and a research plan has been outlined. When determining the method of data collection for the study, the researcher needs to consider two types of data: primary and secondary (Gujarati & Porter, 2022). This study uses a secondary data collection method attained from various resources about the data of the firm's financials, stock prices, and some macroeconomic indicators. The data is taken from various sources and published on authentic sources. Hence, data validity remains intact, and the results extracted from this data can be generalized.

3.11 Operationalisation of Variables

A total of fifteen variables were used in this study. Stock returns are the dependent variable, and investor sentiments are the latent independent variable measured by different proxies such as share mispricing, bond yield spread, gold bullion, consumer confidence index, turnover, advance-decline ratio, and relative strength index. This study follows previous studies to include some controlling variables: firm-specific and macroeconomic variables. The firm-specific variables include sales growth, financing structure, and size. The macroeconomic variables include inflation, interest rate, and unemployment level. Another variable of this study is stock return volatility.

3.11.1 Dependent Variable

Stock Return. The two most commonly utilized formulas to measure stock returns are arithmetic and logarithmic return, calculated as:

In arithmetic return, stock return is the percentage change in stock prices (Siddikee, 2018):

$$R_{i,t} = \frac{(P_t - P_{t-1})}{P_{t-1}} \tag{3.1}$$

where Ri,t is the stock return of i security at time t, Pt is the ending stock price, and Pt-1 is the beginning stock price.

In logarithmic return, stock return is the logarithm of the percentage of today's stock price to the previous day's stock price (Reis & Pinho, 2021; Siddikee, 2018):

$$R_{i,t} = ln(\frac{P_t}{P_{t-1}}) \tag{3.2}$$

where $R_{i,t}$ is the stock return of i security at time t,

ln is logarithm

P_t is the ending stock price, and P_{t-1} is the beginning stock price.

The formulas presented in equation 1 and equation 2 assess the variation in stock return of security at short periods such as daily, weekly, monthly, and quarterly. Comparatively, the return calculated through logarithmic return is more widely utilized than that calculated through arithmetic return. Logarithmic return is a superior method for calculating returns because of its time-saving traits, as it can assess numerous days simultaneously with its additive and symmetrical properties. Moreover, the logarithm returns remain stable with continuous compounding in comparison to arithmetic returns with discrete compounding. The discrete compounding can produce discrepant results, particularly with shorter time intervals. The formula of logarithm returns is percentage change, which makes it comparable and interpretable across different periods. It assesses the returns irrespective of the asset price magnitude. While analysing the volatility and risk, the logarithm returns are used to give more reliable results. There is consistency in the logarithm return with the geometric mean. The geometric mean is appropriate for measuring average returns over numerous periods (Siddikee, 2018). Therefore, logarithm returns are preferred due to their statistical advantages and mathematical properties.

However, this formula is adjusted for changes in capital structure i.e., dividend, bonus shares, and right issues (King, 1966; Maingi & Waweru, 2022; Patell, 1976; Siddikee, 2018) as:

$$R^{*}_{i,t} = \frac{S_t}{S_{t-1}} \left\{ P_t \left(1 - \frac{RI_t SP_t}{S_{t-1} PR_t SP_t} \right) + D_t \right\} \qquad (3.3)$$

Where, S_t = Number of shares outstanding at time t

S_{t-1} = Lag of S_t

P_t = Closing price at time t

RI_t = Shares issued through right at time t

SP_t = Subscription price for right at time t

PR_t = Stock price at time of right

D_t = Cash dividend at time t

This formula is used in calculation of stock returns with right shares, bonus shares and dividends otherwise the formula given in equation 2 is used in calculation of stock returns.

3.11.2 Independent Variables

Behavioural finance involves several challenging aspects, one of which is measuring investor sentiments. Although the majority of earlier research has shown in theory how investor sentiments affect the stock price, a single indicator has yet to be developed to assess investor sentiments. When creating the investor sentiments index in the past, academics typically copy the proxy indicators chosen by international scholars, using the same proxy variables under all conditions. It is almost impossible to guarantee that investor sentiment proxy variables work in all market conditions. Therefore, this study argues that no universal investor sentiment proxy variables exist. Instead, the chosen proxy variables must be based on the specific circumstances (He *et al*., 2017). Therefore this study uses share mispricing (Giglio & Kelly, 2018; Reis & Pinho, 2021; Zhou, 2018; Zhou & Yang, 2020), bond yield spread (F. Hussain & Mahmood, 2017; Reis & Pinho, 2021), gold bullion (Baur & Lucey, 2010; Baur & McDermott, 2010; Da *et al*., 2015; Dyhrberg, 2016; Reis & Pinho, 2021), consumer confidence index (Chui *et al*., 2010; Fisher & Statman, 2003; Jansen & Nahuis, 2003; Kearney & Liu, 2014; Lemmon & Portniaguina, 2006; Reis & Pinho, 2021), shares turnover (Asem *et al*., 2016; Baker & Stein, 2004; Baker & Wurgler, 2006, 2006; Chen *et al*., 2013; Kim & Byun, 2010; Liao *et al*., 2011; Reis & Pinho, 2021; Yang & Zhou, 2015, 2016; Zhou & Yang, 2020), advance-decline ratio (Baker & Wurgler, 2006; Brown & Cliff, 2004; Dash, 2016; He *et al*., 2017; Jitmaneeroj, 2017; Kumari & Mahakud, 2015; Mohapatra, 2022), and relative strength index (Baker & Wurgler, 2006; Chen *et al*., 2010; Reis & Pinho, 2021; Yang & Zhou, 2015, 2016; Zhou, 2018; Zhou & Yang, 2020, 2020) as proxy of investor sentiments measured from market data and survey data.

Share Mispricing. About the proxies of investor sentiments, share mispricing is the variation in share fair price and its market constituent as (Giglio & Kelly, 2018; Reis & Pinho, 2021; Zhou & Yang, 2020):

$$SMP_{i,t} = Market\,Value_{it} - Intrinsic\,Value_{it} \tag{3.4}$$

Where $SMP_{i,t}$ is share mispricing of firms i at time t

This calculation shows that the stock price is at a discount or premium compared to the intrinsic value, which gives insights into the potential investor opportunity. In the case of a positive result, the market value is greater than the intrinsic value, which means the stock is overvalued or trading at a premium price. In a negative result, the market value is less than the intrinsic value, which means the stock is undervalued or trading at a discount price. Therefore, in case of potential mispricing, the investment decisions are based.

The intrinsic value of a share is determined using the Graham formula, a method developed by Benjamin Graham. This approach, rooted in value investing, is widely respected for its ability to estimate intrinsic stock prices as (Graham, 2009; Lin & Sung, 2014; Mohammad, 2022; Rakim *et al*., 2022; Srivastava & Kulshrestha, 2020):

$$Graham\ number = \sqrt{22.5 * EPS * BVPS} \tag{3.5}$$

Where, EPS is quarterly earnings per share calculated from the company's quarterly net income (after-tax) divided by the number of its quarterly outstanding shares. However, BVPS is the quarterly book value per share calculated in terms of the ratio of quarterly equity available to common stockholders against the number of shares outstanding quarterly. This formula presents a simple method of measuring a stock's intrinsic value based on fundamental financial measures. It is a valuable tool for investors with defensive traits. The investors willing to make investments in the market using less point of time, management, and effort are called defensive investors. This method is practical for determining stock prices for any firm regardless of its industry or size. Therefore, this is a well-balanced as well as comprehensive framework which can assess all kinds of firms (Graham, 2009; Lin & Sung, 2014; Mohammad, 2022).

Bond Yield Spread. The bond yield spread is the difference between quarterly ten year and quarterly three-month bond yield calculated as (Hussain & Mahmood, 2017):

$$BON_t = 10yBON_t - 3mBON_t \qquad (3.6)$$

Where BON_t is bond yield spread at time t

$10yBON_t$ is 10-year quarterly bond yield at time t

$3mBON_t$ is 3-month quarterly bond yield at time t

The bond yield spread is a significant indicator in the financial markets, and it is commonly used by policymakers, investors, and analysts to assess the overall economic health and make valuations about potential conditions of the economy. Among the components of bond yield spread, the 10-year bond yield is the interest rate or yield on a 10-year bond issued by the government. It is the yearly return expected by an investor on the bond. Similarly, the 3-month bond yield spread is a short-term bond yield impacted by short-run economic circumstances and state bank policies. In an upward yield curve, the 10-year bond yield exceeds the 3-month bond yield. It is usually deemed a sign of a high return on long-run risk and confidence in the economy's growth, thereby turning investor sentiments toward short-run stock investments. On the other hand, in the inverted yield curve, the 10-year bond yield is less than the 3-month bond yield. It is usually deemed a sign of declining economic growth, thereby turning investor sentiments toward long-run stock investments. Investors are looking for security in long-run bonds, expecting economic challenges. The wide spread of bond yield shows rising perceived risks, signalling economic stability concerns. In contrast, the narrow spread of bond yield shows improved economic sentiment. Investors use the information of this yield spread for decision-making about the allocation of assets (Reis & Pinho, 2021). The change in the spread level impacts investment strategies, specifically for those seeking signals of prospective market shift.

Gold Bullion. Gold bullion is measured as the quarterly closing price of USD gold multiplied by the exchange rate to convert it into Pakistani rupee (Reis & Pinho, 2021) and then taking its percentage change as:

$$\Delta\, Gold_t = \frac{(Gold_t - Gold_{t-1})}{Gold_{t-1}} \quad (3.7)$$

Where, Δ $Gold_t$ is the change in price of gold at time t

$Gold_t$ is price of gold at time t

$Gold_{t-1}$ is previous price of gold

The use of gold bullion as an investor sentiment proxy captures the impact of gold price globally and changes in the exchange rate on the expected gold value of investors in the Pakistan market. A positive change shows an increase in gold bullion price; however, a negative change shows a decrease in gold bullion price. Such changes show changes in investor sentiments for gold and, ultimately, for stocks. The rising price of gold shows an increasing preference for it as a safe-haven asset in response to worldwide economic fluctuations (Baur & McDermott, 2010; Dyhrberg, 2016). In addition, changes in the exchange rate may impact the gold price for Pakistani investors, so the currency fluctuation due to the exchange rate can influence investors. In this way, there are shifts in the investor's behaviour by catering to both local and global factors to impact the perceptions of investors for considering gold as an investment opportunity (Baur & Lucey, 2010; Da *et al*., 2015; Dyhrberg, 2016).

Consumer Confidence Index. CCI is a survey sentiment measure and a significant Organization for Economic Corporation and Development (OECD) indicator. It forecasts future household consumption and savings trends by conducting comprehensive surveys on consumers' financial expectations, overall economic sentiments, unemployment concerns, and their ability to save. When the CCI surpasses 100, it signifies robust consumer confidence in the future, leading to a higher inclination towards significant purchases in the subsequent year. On the other hand, a value below 100 indicates pessimism in the air. It is used to test each measure's impact on the stock returns instead of a joint index in empirical research (Qiu & Welch, 2004). This approach is extended in this study by combining single investment sentiment proxies based on the market data and reviewing the latest work on the sentiments based on the framework defined by the research study of Kearney & Liu (2014). CCI is used extensively as an investor sentiment proxy (Chui *et al*., 2010; Fisher & Statman, 2003; Jansen & Nahuis, 2003; Lemmon & Portniaguina, 2006). The State Bank of Pakistan (SBP) conducts the CCI survey quarterly. The survey sample comprises a rotating panel comprising one-third of the respondents, as those households were surveyed six months ago. However, the remaining two-thirds of the respondents are new. In this way, the stratification survey scheme is applied in the rotating panel. The index calculation is made from the results of the SBP survey report of businesses, households, and other perception surveys in the form of a Diffusion Index. This index reveals the overall tendency of respondents regarding a particular aspect of a specific survey. The survey questionnaire has closed-ended questions comprise of 5 options for each question to be responded as (SBP, n.d.):

1. PP = Improve/ increase significantly
2. P = Improve/ increase
3. E = Unchanged/ neutral
4. N = Deteriorate/ decline
5. NN = Deteriorate/ decline significantly

Based on these options, the diffusion index is calculated in following steps: the first step, net response is calculated as:

$$NR = (1.00 * PP) + (0.50 * P) + (-0.50 * N) + (-1.00 * NN) \tag{3.8}$$

The second step, diffusion index is calculated as:

$$DI = (100 + NR) / 2 \tag{3.9}$$

Where, DI value ranges from 0-100, which can be interpreted as:

DI > 50, which shows that the percentage of negative views are less than positive views

DI = 50, which shows that the percentage of negative views are equal to positive views

DI < 50, which shows that the percentage of negative views are more than positive views

The index of CCI is further estimated as:

$$\Delta\, CCI_t = \frac{(CCI_t - CCI_{t-1})}{CCI_{t-1}} \qquad (3.10)$$

Where, ΔCCI_t is the change in price of CCI at time t

CCI_t is price of gold at time t

CCI_{t-1} is previous price of CCI

CCI is usually associated with an economic viewpoint. Consumers spend, invest, and participate in the financial markets when anticipating an optimistic future. This sentiment spreads into investor sentiments, impacting their market confidence and becoming optimistic for the stock market (Qiu & Welch, 2004). The change in consumer confidence impacts the perceptions of risk in the market. In the case of optimistic consumers, investors identify less economic risk and confidence regarding investment risks. Optimistic consumer sentiment supports an optimistic viewpoint on the firm performance. Investors search for vital confidence signs to indicate potential firm success and, as a result, high stock prices. It is deemed a critical economic indicator to predict future trends in the market. The consumer confidence changes are noticed as an indication of probable changes in investor sentiments. Overall, the psychology of the market is contributed by consumer confidence. Investor sentiments are impacted by the combined mood of the market players; thereby, positive confidence contributes to bullish sentiment (Chui *et al*., 2010; Kearney & Liu, 2014).

Turnover. Share turnover is the share volume to the number of shares issued. Share turnover is the sum of quarterly traded shares in the stock exchange (Chen *et al*., 2013; Kim & Byun, 2010; Liao *et al*., 2011; Yang & Zhou, 2015, 2016).

$$TURN_{i,t} = \frac{Share\ turnover_{i,t}}{Outstanding\ shares_{i,t}} \tag{3.11}$$

where turn stands for share turnover,

i stands for firms and

t stands for time period

This ratio gives meaningful insights into the market activity and is a proxy for the sentiments of investors (Asem *et al*., 2016; Baker & Stein, 2004; Baker & Wurgler, 2006; Zhou & Yang, 2020). The higher the ratio, the more active the stock trading is, which shows investors are enthusiastically purchasing and then letting off shares. It is a sign of increased interest in investors and stock engagement. However, the lower the ratio, the more stable the sentiments are. In a low turnover ratio, investors must react more vigorously to the events, market environmental changes, and other events, indicating moderately steady investor sentiment. The turnover rate increases market liquidity, which increases with investor sentiments (Kim & Byun, 2010).

The principles of behavioural finance propose that investor sentiments impact trading behaviour. Assessing share turnover gives insight into how psychological factors influence market activity. Substantial changes in share turnover are linked with particular events like mergers, releases, and regulatory developments. Considering the perspective of these events provides profound insights into investor sentiments (Asem *et al*., 2016; Zhou & Yang, 2020).

Advance-Decline Ratio. The ADR ratio, a key metric in financial analysis, is a fraction that measures the breadth of the market by considering the number of quarterly advancing and declining stocks. This ratio is calculated by dividing the sum of advancing stocks in the quarter by the sum of declining stocks in that quarter. It's a crucial tool for understanding market dynamics (Baker & Wurgler, 2006; He *et al*., 2017).

$$ADR_{i,t} = \frac{Number\ of\ advancing\ stocks_{i,t}}{Number\ of\ declining\ stocks_{i,t}} \tag{3.12}$$

where ADR stands for advance-decline ratio,

i stands for firms and

t stands for time period

The value above 1 shows bullish sentiments as the trend of the market is moving in an increasing direction since the number of advancing stocks is more than the number of declining stocks. It is a sign that investment sentiments have an optimistic perspective. However, a value of less than 1 indicates bearish sentiments as the market trend is decreasing since the number of advancing stocks is less than the number of declining stocks. It is a sign that investment sentiments have a pessimistic perspective. Therefore, this ratio gives insights into investor sentiments, market trends, and the market health (Brown & Cliff, 2004; Dash, 2016; Jitmaneeroj, 2017; Kumari & Mahakud, 2015).

Relative Strength Index. RSI is an offshoot of the momentum indicator, which measures the speed and variation in price movements. It is usually based on a span of 14 days. RSI meticulously measures price fluctuations to evaluate overbought or oversold securities from 0 to 100. It is considered as an investor sentiment proxy (Baker & Wurgler, 2006; Yang & Zhou, 2015, 2016; Zhou & Yang, 2020).

$$RSI_{i.t} = 100 - \left(\frac{100}{1 + \frac{Average\ gain_{i,t}}{Average\ loss_{i,t}}} \right) \tag{3.13}$$

where RSI stands for relative strength index

i stands for firms and

t stands for time period

The first calculation for average gain and loss are simple averages of each stock price. First, the average gain is the sum of gains over the period divided by the number of days (t). Similarly, the first average loss is the sum of losses over the past period divided by the number of days in that period (t). The second and subsequent calculations are based on the prior averages and the current gain/loss as (Baker & Wurgler, 2006; Yang & Zhou, 2015, 2016; Zhou & Yang, 2020):

$$Average\ Gain_{i,t} = \frac{[(Previous\ average\ gain_i) * (t-1)] + current\ gain_i}{t} \tag{3.14}$$

$$Average\ Loss_{i,t} = \frac{[(Previous\ average\ loss_i) * (t-1)] + current\ loss_i}{t} \tag{3.15}$$

where t is the current time period and t-1 is the previous time period of i firms

If there were an average gain in the previous period and a loss in the current period and vice versa, then the current period's value become zero. After the 14-day window period, the calculation is converted into a quarter by taking an average of the daily RSI value. The window of 14 days is chosen as a period that shows closer to accurate results. When RSI touches or goes beyond 70, it shows a potentially overbought or overestimated security. It proposes that investors are excessively optimistic, with a prospective for correction or reversal. However, an RSI with a value of 30 reverses that trend, i.e., oversold security. It proposes that investors are excessively pessimistic, and there is a prospect for upward correction or rebound (Chen *et al*., 2010; Zhou, 2018).

This moving average method is frequently used in technical analysis to smooth out data fluctuations over time. It provides the average value of change in price to give more easily taken information for analysing and anticipating trends (Chang & Liu, 2008). It helps identify trends by eliminating short-term fluctuations or random noise. An increasing trend occurs when the price movement is above the moving average and vice versa. Past research studies have used a similar method (Appel, 2003; Baker & Wurgler, 2006; Chen *et al*., 2010; Gunasekarage & Power, 2001; Yang & Zhou, 2015, 2016; Zhou, 2018; Zhou & Yang, 2020).

Differences between price movement and RSI give insights into potential changes in the sentiment. For example, if there is a new high in the RSI but not in price, it identifies that bullish sentiments are weakening. If the price rises with RSI, it confirms the upward trend and strengthens the bearish sentiments and vice versa. The analysis in volume (such as turnover) along with RSI gives additional insights. The high value of RSI and high trading volume suggest strong support for bearish/bullish sentiments. Assessing the RSI for extended periods gives insights into sentimental changes and trend sustainability (Yang & Zhou, 2015, 2016; Zhou & Yang, 2020).

3.11.3 Control Variables

Previous studies have undertaken numerous variables to control the probability of omitted variables' bias (Reis & Pinho, 2021). This study uses sales growth (Ajizah & Biduri, 2021; Lau *et al*., 2002; Reis & Pinho, 2021; Yulianto & Mayasari, 2022), financial structure (Ajizah & Biduri, 2021; Reis & Pinho, 2021) and size (Ajizah & Biduri, 2021; Lau *et al*., 2002; Reis & Pinho, 2021) as firm related controlling variables. Moreover consumer price index (Bayram, 2017; Oner, 2023; Oxman, 2012; Reis & Pinho, 2021; Schmeling, 2009; Tiwari *et al*., 2019), interest rate (Alam & Uddin, 2009; Assefa *et al*., 2017; R. Ferrer *et al*., 2016; Lioui & Maio, 2014), and unemployment (Boyd *et al*., 2005; Dunham & Garcia, 2021; Farsio & Fazel, 2013; Pompian, 2012; Zahera & Bansal, 2018) are used as macroeconomic controlling variables.

Sales Growth. Among firm-specific controlling variables, sales are measured as quarterly percentage change as shown in eq. 16 (Ajizah & Biduri, 2021):

$$Sales\ Growth_{i,t} = \frac{Sales_{\ i,t} - Sales_{\ i,t-1}}{Sales_{\ i,t-1}} \times 100 \tag{3.16}$$

Where, i = companies

t = time period

t - 1 = previous time period

The measurement of sales as a firm-specific controlling variable for investor sentiments on stock returns gives a dynamic indicator for the firm's performance related to its revenues. It shows the growth (in case of positive sign) or contraction (in case of negative sign) of the firm, which impacts investor sentiments (Lau *et al*., 2002). This variable is used as a communication strategy for investors in which informative and transparent communication related to the performance of sales (Yulianto & Mayasari, 2022) contributes to the confidence of investors (Reis & Pinho, 2021).

Financing Structure. Financial structure is calculated as the ration of quarterly net debt to quarterly property, plant and, equipment (Reis & Pinho, 2021):

$$FIN_{i,t} = \frac{Net\ Debt_{i,t}}{PPE_{i,t}} \tag{3.17}$$

Whereas, net debt is measured as the difference between total debts and current assets as:

Net debt = Total liabilities – current assets

PPE = Property, plant and equipment

i = companies

t = time period

A positive ratio of financing structure shows that the firm has more net debt than fixed assets, which shows a highly financially leveraged firm. In contrast, an unfavourable ratio of financing structure shows that the firms have less net debt than fixed assets, which shows a less financially leveraged firm or a more conservative capital structure. The level of financial leverage is coupled with financial risk (Ajizah & Biduri, 2021). Investors consider the high ratio of financial structure as a sign of elevated risk, which influences investors' sentiments (Reis & Pinho, 2021).

Firm Size. Firm size is measured in terms of the natural logarithm of quarterly assets as (Reis & Pinho, 2021):

$$SIZ_{i,t} = ln\ (Total\ assets_{i,t}) \tag{3.18}$$

Where, SIZ = size

Ln = natural logarithm

i = companies

t = time period

The method of considering natural logarithms accounts for the company scale as it moderates the influence of extreme values and better represents relative firm sizes. The higher the size value, the more significant the firm size and vice versa. The scale of the firm changes with time, giving insight into the long-run projects and growth lines. Usually, larger firms are considered more stable, while smaller firms are riskier (Ajizah & Biduri, 2021; Lau *et al*., 2002). However, there is no exception that small-sized and riskier firms are growing firms (Reis & Pinho, 2021).

Inflation. The inflation rate is calculated from the consumer price index (CPI) as percentage change in CPI as (Reis & Pinho, 2021):

$$INF_t = \frac{(CPI_t - CPI_{t-1})}{CPI_{t-1}} \quad (3.19)$$

Where INF_t is inflation at time t

CPI_t is the current price of CPI

CPI_{t-1} is the previous price of CPI

It is then converted into quarters using e-views software. In the frequency conversion option, the quadratic approach matches the average of quarterly data converted from annual data. The inflation rate as a macroeconomic variable gives insights into the influence of inflation on a firm's financial performance. The inflation rate is measured through CPI as a measure of the change in prices customers pay for a basket of consumer goods and services (Bayram, 2017). Positive inflation shows that customers' price for a basket of consumer goods and services is increased. This price increase impacts the firm's cost, pricing strategies, and financial performance.

On the other hand, negative inflation shows that prices paid by customers for a basket of consumer goods and services are decreased (Oxman, 2012). This price decrease impacts the firm's cost and the investor's sentiments. The firms implement strategies for overcoming the influence of inflation by adjusting pricing strategies, managing costs proficiently, and making strategic investments (Oner, 2023). Investors foresee how much a firm can mitigate the pressure of inflation, thereby making changes in the investors' sentiments (Reis & Pinho, 2021; Schmeling, 2009; Tiwari *et al*., 2019).

Interest Rate. The interest rate is measured as the 3-month ask price of the Karachi Inter-bank offering rate (KIBOR). KIBOR is an interest rate benchmark showing banks' short-run borrowing costs. The monthly KIBOR is converted into annual by taking the average for a quarter and then converted into quarters. The quadratic approach is used in the frequency conversion option, matching the sum of quarterly data converted from annual data. KIBOR presents the short-run borrowing cost of banks at which banks agreed to lend to each other in the Karachi interbank market. The KIBOR influences the borrowing cost of firms, especially when it comes to short-run finance. The increase in KIBOR increases borrowing costs, thereby impacting firms' profitability. It is also an indication of financial condition and liquidity in the market. High KIBOR signals strict credit conditions; however, low KIBOR is favourable for financing. Firms use the information from KIBOR in investor-firm communication. Transparent communication regarding the impact of interest rates on the cost of capital helps manage investors' expectations. The policies of the central bank, expectations of inflation, and general economic conditions change in KIBOR. This information impacts the factors impacting investor sentiments on the stock returns, especially in the dynamics of interest rate (Alam & Uddin, 2009; Assefa *et al*., 2017; Ferrer *et al*., 2016; Herculano & Lütkebohmert, 2023; Lioui & Maio, 2014).

Unemployment Level. The unemployment level is measured as a percent of the total labour force unemployed, as (Chen *et al*., 2010):

$$Unemployment\ Level_{t} = \%\ (total\ labour\ force\ unemployed)_{t} \qquad (3.20)$$

Where, t = time period

The labour force is without work, but they are looking for and available for work. The yearly unemployment level is converted into quarters. The quadratic approach is used in the frequency conversion option, matching the sum of quarterly data converted from annual data. This variable provides the economic state with the dynamics of the labour market, which influences the performance of firms. In this manner, the job market's health and the economy's overall condition are assessed (Farsio & Fazel, 2013). The high unemployment rate has an inverse relation with consumer spending and consumer confidence, thereby influencing the profitability and revenues of businesses.

In contrast, the low unemployment level is directly related to consumer spending and consumer confidence (Boyd *et al*., 2005). The change in unemployment rate shows a labour market shift, where rising unemployment challenges the economy (Dunham & Garcia, 2021; Zahera & Bansal, 2018). However, it shows economic growth with increasing employment, thereby influencing the sentiments of investors (Chen *et al*., 2010; Pompian, 2012).

3.11.4 Stock Return Volatility

The stock return volatility is measured as the quarterly standard deviation of the population of the logarithm stock returns. It measures how much the returns of a quarter deviate from the mean. High stock volatility shows large fluctuations in the stock price over a quarter. However, low stock volatility shows fewer fluctuations and stable stock returns. The stocks with high levels of volatility are considered riskier investments with uncertain and broad market conditions. Investors and firms utilize volatility measures to manage risk, as managing and understanding volatility is essential for managing effective portfolios (H & Rishad, 2020; Qiu & Welch, 2004; Sayim *et al*., 2013).

3.12 Data Collection and Analysis Procedure

The data related to companies' financial information (share mispricing, sales, financing structure, size) are gathered from the quarterly reports of the companies retrieved from their official websites, PSX, SBP (State Bank of Pakistan), and data stream. The data related to stock prices (stock returns, turnover, advance-decline ratio, relative strength index, volatility) are collected from Business Recorder and PSX. The data related to bond yield are collected from SBP's website. The data related to gold bullion prices are taken from the World Gold Council website. The data related to the consumer confidence index are gathered from the SBP-reports section of the website. The data related to macroeconomic indicators (inflation, interest rate, and unemployment) are gathered from the World Bank website. Once data is collected, it is organized in the Excel sheet to make additional calculations per the variables' definition.

Following the study of Reis and Pinho (2020), KSE-100 index (Pakistani stock market index) companies for the fiscal year 2012 are selected based on their capitalization. These companies are screened for sectors by eliminating financial sector companies due to changes in their business activities. In addition to this, defaulters and non-compliant segments are eliminated from the sample. Attempts are made to search for the missing data from the companies' websites or other official resources to gather as much data as possible. The companies are selected after excluding those having negative equity and profits. This way, 49 companies with active trading, representative sampling, and data representation cover quarterly data on 15-panel variables over eight years from 2012 to 2019.

The choice of high-frequency (quarterly) data rather than yearly data is due to some advantages. The measure of high frequency may seize sudden changes in investors' sentiments. Investors' sentiments are subject to expectations of the subjects about the market. Such expectations are sensitive to minor changes in the information prevailing in the market. The prevailing high-frequency measures of sentiments cannot capture these sudden changes. In addition, empirical research on sentiment focuses on corrections of mispricing by assessing the measures of sentiment annually. Resultantly, it is found that high sentiment periods result in low returns since any mispricing is rectified in the long run.

On the other hand, the measures of low frequency may not commendably seize the process of mispricing and may even need to be appropriately evaluated for the mispricing period. In the case of a perfectly efficient market, there is an immediate correction in mispricing; therefore, sentiments' effect is negative on the short-run returns. Conversely, in the case of a partially efficient or inefficient market, the pressure of trading and mispricing of investor sentiments lasts for a more extended period, and sentiments affect the short-run returns positively. Therefore, the analysis based on high-frequency measures of sentiment may assist in finding whether a correction in mispricing lasts immediately (Seok *et al.*, 2019). However, the choice of highest-frequency (daily) data rather than yearly data has some disadvantages, too. The returns of daily stock can change due to the microstructure noises of the market or due to some transitions in information. In addition, high-frequency data can cover other noises irrelevant to the sentiments. Therefore, owing to the advantages and disadvantages of the highest-frequency data, this study uses quarterly frequency to assess investor sentiments since most variables are available quarterly.

This study eliminates Global Financial Crisis (GFC) and COVID-19 crisis period from the analysis on the basis of theoretical and methodological considerations aimed at enhancing the internal validity of the study's findings. Both the GFC and COVID-19 represent periods of extreme market volatility and structural disruptions that significantly deviate from typical market behaviour. These crises introduce exogenous shocks such as global liquidity crunches, nationwide lockdowns, and unprecedented monetary interventions that may not reflect standard investor sentiment dynamics. Including such periods could introduce structural breaks into the data, violating assumptions of stationarity and distorting econometric estimations (e.g., OLS, or VAR models). Moreover, investor behaviour during crises tends to be driven by fear, panic, or herd behaviour, often influenced by factors beyond economic fundamentals or sentiment indicators typically used in this study (e.g., turnover ratio, trading volume, RSI). These atypical patterns may lead to abnormally high or low sentiment indicators, which can act as outliers and skew the results, reducing the generalizability of the findings to more normal market conditions. During these periods, financial markets were heavily influenced by extraordinary fiscal and monetary policy measures, including bailouts, interest rate cuts, quantitative easing, and regulatory forbearance. These interventions can artificially suppress or amplify market reactions, making it difficult to isolate the true effect of investor sentiment on stock returns. The study aims to investigate typical investor sentiment dynamics in relatively stable or moderately volatile market environments. Including extreme crisis periods shift the focus toward crisis psychology or systemic risk management, which falls outside the intended scope of this research. Furthermore, by excluding these anomalies, the analysis is better positioned to produce more consistent and interpretable results, ensuring that estimated relationships between sentiment proxies and stock returns reflect typical behavioural patterns rather than responses to rare global shocks. This study does not use the era before 2012 since a variable, the CCI, was surveyed in January 2012. It also does not use the era after 2019 since it is the COVID-19-2020 time period. The selection of the sample period from 2012 to 2019 was primarily guided by the availability of the CCI data in Pakistan, which is a proxy in this study to capture macro-level investor sentiment. Since the CCI is only available from 2012 onward, extending the sample backward result in missing data for this key variable, potentially compromising model consistency and comparability across sentiment proxies. While it is acknowledged that other sentiment proxies such as share mispricing, turnover, gold bullion, bond yield spread, and RSI have longer historical availability. Restricting the entire dataset to the 2012–2019 window ensures a uniform analysis across all variables. Introducing different sample periods for different proxies or developing parallel models increase model complexity and potentially introduce bias due to varying economic regimes. Moreover, the selected period provides a relevant and rich context for studying sentiment dynamics in the Pakistani stock market, covering significant events such as post-global financial crisis adjustments, political transitions, and local economic reforms. These years are marked by observable fluctuations in investor sentiment, offering sufficient variation for robust econometric analysis.

This study uses 49 cross-sections and 1464 observations of the unbalanced panel used to assess the relationship between investor sentiments and stock returns. While the dataset used in this study is unbalanced, it arises primarily due to the exclusion of firms with incomplete data at the beginning or end of the sample period (2012–2019). Firms included in the final panel are selected based on the availability of consistent quarterly data across the core years, ensuring temporal continuity and reliability in the estimation. This approach minimizes the severity of typical unbalanced panel issues such as inconsistent time spans, sporadic gaps, or systematic missingness within the time series of individual firms. Moreover, FMOLS is designed to handle non-stationary panel data with cointegration, and previous research (e.g., Pedroni, 2001) indicates that FMOLS still produces asymptotically unbiased and normally distributed estimates under unbalanced panels, provided the missing data is not structurally linked to the error term or the regressors. Since in this study the data is missing only at the margins and not within the main sample period, it does not significantly bias long-run variance estimations or compromise the lead-lag structure in dynamic modeling. Additionally, the exclusion of firms with substantial internal gaps avoids non-random missing data problems, helping to maintain representativeness and robustness. Diagnostic checks for heteroscedasticity and autocorrelation are performed, and necessary corrections are incorporated, further supporting the appropriateness of using FMOLS with the selected panel structure. Furthermore, FMOLS assumes certain properties for the error term such as serial independence, stationarity, homoscedasticity. This study identified the presence of heteroskedasticity in the residuals. Additionally, diagnostic tests confirm that other assumptions, including serial independence and long-run variance consistency, are reasonably satisfied. FMOLS automatically adjusts for serial correlation and heteroskedasticity in the long-run variance of the residuals. Thus, although one error term assumption is violated, appropriate methodological adjustments ensure the validity and robustness of the long-run FMOLS estimations. The methodological approach combined with diagnostic tests and robustness adjustments ensures that these assumptions are reasonably met. Thus, the potential issues associated with the error term in FMOLS are acknowledged and effectively addressed, supporting the validity of your long-run estimations.

This research is carried out in four different steps. The first step is to carry out descriptive statistics and other diagnostic tests covering unit root tests, multicollinearity tests, autocorrelation tests, heteroscedasticity tests, and endogeneity tests. The second step is implementing a cointegration test to assess the short-run and long-run relation between factors. The third step is to carry out the fully modified ordinary least square regression model to test the long-run relation between stock returns and investor sentiments. Following the literature studies, the fourth step is to test the bi-directional relation using lag order selection criteria, the Granger causality models, and the VAR model (Agyemang & Bardai, 2022; Gharbi *et al*., 2022).

3.13 Data Analysis Statistical Methods and Software

This study uses a quantitative approach to analyse the secondary data. Despite limited examples of panel data approaches in studying the impact of investor sentiments on stock returns, this research relies on the comprehensive methodology employed by Chen, Chen, & Lee (2013); Ni, Wang, & Xue (2015); Schmeling (2009) and Zouaoui, Nouyrigat, & Beer (2011).

3.13.1 Cointegration Relationships

Variables are defined as cointegrated if the linear combination of these variables is stationary. Many time series are not stationary but move together with time. Some effects on the market forces series show that the two sets of series are unavoidable by certain relationships for a long time. Cointegrating relations are considered an equilibrium or long-term phenomenon as it is likely that cointegrating variables move away from their relationship in a short period; however, they show proposed returns over a long period (Brooks, 2019).

Financial theory recommends that two and more than two variables are likely to hold some long-term relationship with each other. In order to deal with financial and economic data related to time series, it takes work to cater to non-stationary variables. The non-stationary variables have unit roots or trends, making extracting meaningful relationships hard. There is a long-term linear and stable combination of relationships between variables. Cointegration is typically used in finance, specifically in researching pair trading strategies. For example, if two stocks are cointegrated, the long-run relationship is deviated to form trading opportunities. The literature states that the techniques for modelling panel cointegration are still in the initial stages. However, the unit root is relatively mature for testing of the panel. The tests for modelling panel cointegration are complex due to the probability of cointegration among the group of variables (cross-sectional cointegration) and within the groups (Brooks, 2019).

The cointegration test evaluates the correlation of numerous time series in the long run. Clive Granger and Robert Engle invented this idea once the theory of spurious regression was published. It points out scenarios in case two or more time series are combined so that they do not move away from the equilibrium in the long run. The two-step Engle-Granger test starts by creating residuals based on static regression and testing residuals for the unit root analysis. The tests are utilized to determine the sensitivity of two variables over time. Economists depend on linear regression to find the relationship between different time series. Newbold and Granger argue that linear regression needs to be corrected in assessing time series data because of the likelihood of reaping spurious correlation. This correlation takes place when two or more two related variables are considered causally related because of an unfamiliar factor or a coincidence. The outcome is a deceptive statistical relation among time series variables. The vector approach of Engle and Granger states that the non-stationary and time series data are related to each other and cannot move away from equilibrium in the long run (Brooks, 2019).

The authors further argue that linear regression assesses the relationship between some time series variables since detrending cannot address the problem of spurious correlation. Instead, the scholars recommend looking for the time series non-stationary data cointegration. They argue that two or more time series variables with a trend of I (1) can be cointegrated if a relationship exists between variables. Among the different methods for testing cointegration are the Johansen test, the Phillips-Quliaris test, and the Engle-Granger test. This study follows the Engle-Granger test, which uses the Augmented Dickey-Fuller test (ADF) and other tests in time series stationarity units. In the case of the time series cointegration, the Engle-Granger test shows that the residuals are stationary (Brooks, 2019). The null hypothesis of this test is that the regression residuals have a unit root (Ho: ρi= 1), which means no cointegration (Brooks, 2019).

3.13.2 Fully Modified Ordinary Least Square Analysis

There are two types of panel data analysis: static model and dynamic model. This study falls in the dynamic modelling, an advanced approach with some criteria and steps. Dynamic modelling may include lagged dependent or independent variables to capture time dependence. Dynamic modelling may also transform variables by taking differences over time to address non-stationarity. Fully modified ordinary least square (FMOLS) is a dynamic panel data analysis technique of financial econometrics. This test is optimal for time series data where non-stationary variables are present. The technique requires assessing the FMOLS techniques for long-run coefficients and making the model efficient and consistent in serial correlation, endogeneity, and heteroscedasticity. This analysis technique extends the two-step model of the Engle-Granger by considering the endogeneity of the regressors (Brooks, 2019).

The FMOLS has been introduced by Phillips and Hansen (1990), which is a technique to improve accuracy of long-term economic relationships (cointegration equations). It helps correct three common statistical problems: endogeneity, autocorrelation, and heteroscedasticity. FMOLS uses instrumental variables to fix endogeneity and applies a weighting system to adjust for heteroscedasticity. The term "fully modified" means that the method corrects biases by using differences in independent variables, ensuring more accurate and reliable estimates (Gujarati & Porter, 2022). The preliminary estimator is calculated using a 1-way symmetric covariance matrix, which helps assessing the variation in long-run residuals. This estimator is efficient and unbiased, it provides a reliable estimate of the true value, even when applied to large datasets. When data set is increase, the estimator follows a normal distribution, meaning that its results become more statistically stable and predictable. It allows for accurate standard deviations, which are essential for interpreting results and making sound statistical conclusions. In this way, the t-test of FMOLS provides adequate validity for long-run coefficients. In addition, this method serves well even in small sample sizes and provides efficient results (Brooks, 2019; Gujarati & Porter, 2022; Karimzadeh khosroshahi *et al*., 2021).

This study uses the Fully Modified Ordinary Least Square (FMOLS) approach, analogous to Engel-Granger's technique (Agyemang & Bardai, 2022; Hardi *et al*., 2023; Hardia & Rezeki, 2024; Pasha & Ramzan, 2019; Tetteh *et al*., 2019; Trichilli *et al*., 2020). There is two-steps procedure of Engle-Granger in which all variables are assumed to have the first difference in stationarity I (1). The first step covers (Brooks, 2019):

Ordinary Least Square (OLS) is estimated when a cointegration relationship exists between the dependent variable and its fundamentals, as shown in equation 21.

$$X_{it} = \alpha_i + \beta Y_{it} + \varpi_{it} \tag{3.21}$$

where I = 1, 2, 3,…, N, t = 1, 2, 3,…, T, β = slope, ϖ_{it} = stationary distribution

Once the regression equation is run, the error or residual is estimated termed as error correction term. The unit root is estimated for the error (Gujarati & Porter, 2022). It is required to be stationary at level. Therefore, if all variables are stationary at first difference I (1) and error term is stationary at level I (0), then cointegration exists and there is long-run relationship between variables. The second step covers (Brooks, 2019):

Short run regression model is estimated when a cointegration relationship exists between the dependent variable and its fundamentals as shown in equation 20.

$$\Delta X_{it} = \alpha_i + \beta \, \Delta Y_{it} + \gamma \, ECT_{t-1} \, \epsilon_t \qquad (3.22)$$

where i represents company, t represents time, Δ represents difference of dependent variable, β represents short run coefficients. γ represents residual coefficient, and ECT_{t-1} represents lag of error correction term. If the coefficient of ECT (γ) is negative and significant, then the model adjusts itself to the long run (Brooks, 2019).

The FMOLS model tests relationship of investor sentiments with the stock returns using lagged differences and stationary residuals. The model is expressed as:

$$R_{i,t} = \beta_0 + \beta_1 SMP_{i,t} + \beta_2 BON_t + \beta_3 GOLD_t + \beta_4 CCI_t + \beta_5 TURN_{i,t} + \beta_6 ADR_{i,t} + \beta_7 RSI_{i,t} + \beta_8 SALES_{i,t} + \beta_9 FIN_{i,t} + \beta_{10} SIZ_{i,t} + \beta_{11} INF_t + \beta_{12} INT_t + \beta_{13} UNEMP_t + \beta_{14} VOL_t + \mu_t \qquad (3.23)$$

where i represents company, t represents time, β is regressor coefficient, R is stock returns, SMP is share mispricing, BON is bond yield spread, GOLD is gold bullion, CCI is consumer confidence index, TURN is share turnover, ADR is advance-decline ratio, RSI is relative strength index, SALES is sales growth, FIN is financial structure, SIZ is size, INF is inflation, INT is interest rate, UNEMP is unemployment level, VOL is stock return volatility and μ is error term.

FMOLS is usually implemented using statistical software such as R, Stata, and E-views. This research study uses E-views 12 software tool as the choice of software depends on the familiarity of the software and the particular analysis requirements. When FMOLS is applied in this study, the role of investor sentiments on the PSX-listed firms is found. It also helps deal with expected cointegrating relationships in the presence of endogeneity and time series issues.

3.13.3 Lag Length Selection Criteria

From the perspective of analysis in time series data, especially when analysing a causality test, selecting the proper lag order is fundamental. The lag order selection criteria help determine the number of lags covered in the causality model. The commonly used selection criteria and the criteria choice depend on the data-set characteristics and the particular goals of the under-considered analysis. The likelihood ratio (LR) test makes a comparison of causality with p-lags and respective p-1 lags. The criteria for selecting lag order cover the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQIC), and Final Prediction Error (FPE). Among these criteria, the AIC stabilizes the fit model with the model complexity with the formula (Brooks, 2019):

$$AIC = ln\ (\hat{\sigma}^2) + \frac{2k}{T} \tag{3.24}$$

The lower value of AIC shows a better choice between the complexity and fitness of the model. However, BIC deals with the complexity of the model more intensely in comparison to AIC with the formula (Brooks, 2019):

$$\mathrm{BIC} = \ln\ (\hat{\sigma}^2) + \frac{k\ln(T)}{T} \tag{3.25}$$

The characteristic of BIC is to support a model having superficial characteristics. Moreover, HQIC is quite similar to that of AIC. However, it has a drawback of the complex model with the formula (Brooks, 2019):

$$HQIC = ln\ (\hat{\sigma}^2) + \frac{2k\ ln(ln(T))}{T} \tag{3.26}$$

Another lag order selection criterion is FPE, which inversely relates to the probability of making good predictions for unavailable data. It has the formula (Brooks, 2019):

$$FPE = \left(\frac{T+k+1}{T-k-1}\right)\ \hat{\sigma}^2 \tag{3.27}$$

The Granger causality model is estimated with numerous orders or lags (usually starting from 1) up to a specific maximum lag, usually based on the frequency of data (i.e., yearly, semi-annually, quarterly, monthly, or daily). The lag order is selected that curtails the criteria for selection, or a combined criteria is selected for making a robust decision. The quarterly data is used in most research examining causal relations, and as a rule of thumb, the maximum lag used is 8 (Brooks, 2019; Jones, 1989). This selection of lag order choice has implications for the efficiency and precision of the model. Therefore, cautious thought is needed (Brooks, 2019).

3.13.4 Granger Causality Model

The Granger causality test is a statistical hypothesis used to estimate whether a time series can predict another time series (Brooks, 2019). The directional relation is explored in Granger causality between investor sentiments and stock returns. The concept behind Granger causality is that the Y variable causes X variables, and then past values of Y contain information that helps in predicting X. The null hypothesis of Granger causality for the relation between investor sentiments and stock returns is that the past values of investor sentiments do not cause Granger to. The alternate hypothesis of Granger causality for the relation between investor sentiments and stock returns is that the past values of investor sentiments Granger cause stock returns (Gujarati & Porter, 2022).

The data for stock returns and investor sentiments is pre-processed appropriately for time series to prepare the data for appropriate lags. The lag order (κ) must be selected for the Granger causality test, which shows the past observations to be included in the analysis. A lag order is chosen based on theoretical considerations, such as 8 in the case of quarterly data, and then (κ) lag order is used based on selection criteria (AIC, BIC, HQIC, and FPE) for lag order. The lag order selected criteria are estimated for investor sentiments and stock returns up to the chosen lag order. The next step is to perform the F statistics to compare and contrast the Granger causality model fitness with the investor sentiments and stock returns against a restricted model, eliminating the previous values of investor sentiments. The outcomes of F statistics are evaluated for the significance level. If the p-value of F statistics is significant, then the previous values of investor sentiments are said to Granger cause stock returns. Granger causality does not indicate a structural or direct causal relationship but rather a predictive relationship based on time-based preference. It is essential to consider the lag order choice in Granger causality to evaluate the robustness of various lag specifications. The Granger causality is also sensitive and can be interpreted as evidence of a precise causal relationship within the time series framework (Brooks, 2019).

3.13.5 Vector Autoregressive Model

A vector autoregressive (VAR) model is one among the multivariate time series models proposed by Sims (1980) to predict the relation between investor sentiments and stock returns (Brooks, 2019). This model is highly worthwhile due to its ease of use, flexibility, and proper explaining the dynamic behaviour of financial and economic time series. It is also an adequate forecasting tool for assessing the combined behaviour of numerous interrelated time series variables. The term "vector" shows that the model is a system of equations in the representation of vectors such as (Brooks, 2019):

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_N Y_{t-N} + \varepsilon_t \tag{3.28}$$

Where, Y_t is a vector for present values of variables

Y_{t-1}, Y_{t-2} is a vector for lag values of variables

A_1 and A_2 are coefficient matrices

N is the lag length

ε_t is a vector of white noise errors.

The "autoregressive" is a term that shows that each variable in the model is regressed on its own lagged values and other lagged values of other variables in the model. In simple words, the present value of each variable is modelled in a linear combination of its past values and past values of other variables. VAR models assume stationary time series data, which shows that the statistical properties of the variables remain the same over time. However, taking the first differences of variables is not required as the VAR model incorporates the lagged values of the pessimism index. The parameters of the VAR model cover the coefficients in the lagged terms and are estimated using Ordinary Least Square (OLS) or maximum likelihood estimation methods. This model allows for impulse response analysis, which shows how shocks to a variable spread through the system over time, which helps to understand the dynamic interactions among the variables (Brooks, 2019).

In summary, this study contributes to the empirical evidence about the role of investor sentiments on the stock returns of Pakistan Stock Exchange-listed firms. By using robust quantitative techniques based on positivism, this research strives to create objective relations and patterns in order to enhance the comprehension of the financial behaviour of Pakistan Stock Exchange-listed firms in a deductive approach. The panel data modelling technique applied to the study is a fully modified ordinary least square, which covers the standard OLS regression adjustment to cater to probable concerns like heteroscedasticity, autocorrelation, and endogeneity. Furthermore, using the VAR model, the Granger causality model is proposed after lag order selection and testing of the lead-lag relation between investor sentiments and stock returns.

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CHAPTER 4

RESULTS AND FINDINGS

This research study aims to analyse the impact of investor sentiments on the stock returns of Pakistan Stock Exchange-listed firms. In order to fulfil this aim, the empirical tests are conducted based on the research philosophy, research paradigm, research design, sampling technique, data collection procedure, and data analysis techniques outlined in Chapter 3 of this study. These empirical tests are run on E-views, a data analysis software to empirically test the hypotheses. For this purpose, the results are generated and reported in the sequence of descriptive statistics, unit root test, multicollinearity test, autocorrelation test, heteroscedasticity test, endogeneity test, and cointegration test. Based on these diagnostic tests, the panel regression tests the hypotheses formulated in Chapter 2. Furthermore, the volatility is also examined in this chapter. The causal relationship between investor sentiments and stock returns is also tested in this chapter. These hypotheses are accepted or rejected based on the significance of the results, while reasonable interpretation and justification of the results are provided. This chapter provides detailed information about the interpretation of the results of this research study. However, the discussion of these results is made separately in Chapter 5.

4.1 Diagnostic Testing

4.1.1 Descriptive Analysis

The descriptive analysis precisely provides information about the descriptive quantities to give a general idea of the data set. The data is presented concerning central tendency and variation. The central tendency covers mode, median, and mean. In addition, the variation covers standard deviation and variance (Bell *et al*., 2022). This spread also covers skewness, kurtosis, and minimum and maximum values. The descriptive measures of this study are described in the results table reported as Table 4.1.

Table 4.1

Descriptive Statistics

n = 1464	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Sig. of Jarque-Bera
R	0.028	0.019	1.235	-1.980	0.193	-0.251	12.734	0.000
SMP	0.097	-0.013	111.797	-65.703	4.813	9.536	268.528	0.000
BON	0.021	0.022	0.041	-0.025	0.012	-1.766	7.592	0.000
GOLD	0.019	-0.002	0.259	-0.224	0.093	0.239	4.055	0.000
CCI	0.015	0.013	0.249	-0.184	0.083	0.386	3.829	0.000
TURN	0.113	0.041	1.997	0.000	0.194	3.265	16.669	0.000
ADR	1.007	0.960	5.000	0.000	0.383	3.497	30.068	0.000
RSI	50.014	49.348	99.780	1.004	13.731	0.107	3.241	0.042
SALES	0.050	0.025	3.280	-0.646	0.214	9.586	123.501	0.000
FIN	0.725	0.287	90.947	-118.247	8.148	-6.242	132.894	0.000
SIZ	10.256	10.223	13.620	7.468	1.217	0.247	2.750	0.000
CPI	0.015	0.015	0.034	0.005	0.007	0.554	2.592	0.000
INT	0.022	0.024	0.038	0.015	0.006	0.642	2.942	0.000
UNEMP	0.008	0.009	0.010	0.002	0.002	-0.945	2.676	0.000
VOL	0.020	0.019	0.217	0.000	0.008	9.975	218.895	0.000

Table 4.1 shows that n = 1464, which means that the sample size covers 1464 quarterly observations as a unit of analysis. Furthermore, it shows the mean value of stock returns as 0.028 with a standard deviation of 0.193, which means 2.8% is the average quarterly stock return in the non-financial listed firms of Pakistan. The minimum and maximum values of stock returns during the sample period are -1.980 and 1.235, respectively. The values of skewness and kurtosis for stock returns are -0.251 and 12.734, respectively, which shows that the spread of data for stock returns falls within the normal range of ±1 however, the height of data for stock returns does not fall within the normal range of ±3 (Bell *et al.*, 2022). The Jarque-Bera statistics for stock returns have significant probability values, which shows that the stock returns data has a non-normal distribution.

Table 4.1 further shows the mean value of share mispricing of 0.097 with a standard deviation of 4.813, which means 9.7% is the average quarterly share mispricing for the financial listed firms of Pakistan. The positive mean value of share mispricing shows that the market value is greater than the intrinsic value, which means the stock is overvalued or trading at a premium price. The minimum and maximum values of share mispricing are -65.037 and 111.797, respectively. The skewness and kurtosis values for share mispricing are 9.536 and 268.528, respectively, which shows that the spread and the height of data for share mispricing do not fall within the normal range. The Jarque-Bera statistics for share mispricing have a significant probability value, showing that the share mispricing data is non-normal.

Table 4.1 illustrates the mean value of the bond yield spread is 0.021 with a standard deviation of 0.012, which means 2.1% is the average quarterly bond yield spread. The positive mean value of the bond yield spread shows an upward yield curve, a sign of high return on long-run risk and confidence in the economy's growth, thereby turning investor sentiments toward short-run stock investments. The minimum and maximum values of bond yield spread are -0.025 and 0.041, respectively. The skewness and kurtosis values for bond yield spread are -1.766 and 7.592, respectively, which shows that spread and the height of data for bond yield spread do not fall within the normal range. The Jarque-Bera statistics for bond yield spread have a significant probability value, which shows that the data of bond yield spread is non-normal.

The data in the table indicate that the mean value of gold bullion is 0.019 with a standard deviation of 0.093, which means that 1.9% is the average quarterly change in gold bullion for the financial listed firms of Pakistan. The positive mean value of gold bullion shows that the change in the price of gold bullion increases every quarter. Gold bullion's minimum and maximum change values are -0.224 and 0.259, respectively. The skewness and kurtosis values for gold bullion are 0.239 and 4.055 respectively, which shows that the data spread falls within the normal range and the height of data for gold bullion does not fall within the normal range. The Jarque-Bera statistics for gold bullion have a significant probability value, showing that the gold bullion data is non-normal.

According to the table 4.1, the mean value of the consumer confidence index is 0.015 with a standard deviation of 0.083, which means 1.5% is the average quarterly change in the consumer confidence index for the financial listed firms of Pakistan. The mean value of consumer confidence index is 48, which shows pessimism in the confidence level. However this study uses percentage change in consumer confidence index and the positive mean value of percentage change in consumer confidence index shows encouraging improvement in confidence of investors over the quarters. The minimum and maximum values of change in the consumer confidence index are 0.013 and 0.249, respectively. The skewness and kurtosis values for the consumer confidence index are 0.386 and 3.829, respectively, which shows that the spread of data falls within the normal range and the height of data for the consumer confidence index does not fall within the normal range. The Jarque-Bera statistics for the consumer confidence index have a significant probability value, showing that the data is non-normal.

The table 4.1 highlights mean turnover value is 0.113 with a standard deviation of 0.194, which means 11.3% is the quarterly turnover for the financial listed firms of Pakistan. This low mean turnover value shows investors must actively buy and sell shares. The minimum and maximum values of turnover are 0 and 1.997, respectively. The skewness and kurtosis values for turnover are 3.265 and 16.669, respectively, which shows that the spread and height of data for turnover do not fall within the normal range. The Jarque-Bera statistics for turnover have a significant probability value, which shows that the data on turnover is non-normal.

It is evident from the table 4.1 that the mean value of the advance-decline ratio is 1.007 with a standard deviation of 0.383, which means, on average, the number of advancing stocks is equal to the number of declining stocks in a quarter for the financial listed firms of Pakistan. The mean value of more than 1 shows a bullish market trend as the market moves toward advancing stocks. The minimum and maximum values of the advance-decline ratio are 0.000 and 5.000, respectively. The skewness and kurtosis values are 3.497 and 30.068, respectively, which shows that the spread and the height of data for the advance-decline ratio do not fall within the normal range. The Jarque-Bera statistics for the advance-decline ratio have a significant probability value, which shows that the data for the advance-decline ratio is non-normal.

As presented in the table 4.1, the mean value of the relative strength index is 50.014 with a standard deviation of 13.731. The mean value shows that neither securities are oversold or overbought. The minimum and maximum values of the relative strength index are 1.004 and 99.780. The skewness and kurtosis values for the relative strength index are 0.107 and 3.241, respectively, which shows that the spread of data for the relative strength index falls within the normal range and the height of data for the relative strength index does not fall within the normal range. The Jarque-Bera statistics for the relative strength index have a significant probability value, which shows that the data for the relative strength index is non-normal.

The findings displayed in the table 4.1 reveal that the mean value of sales growth is 0.050 with a standard deviation of 0.214, which means, on average, 5% of the quarterly growth in sales of the financial listed firms in Pakistan. The minimum and maximum values of turnover are -0.646 and 3.280, respectively. The skewness and kurtosis values are 9.586 and 123.501, respectively, which shows that the spread and the height of data for sales growth do not fall within the normal range. The Jarque-Bera statistics for sales growth have a significant probability value, which shows that the data for sales growth is non-normal.

The table 4.1 demonstrates that the mean value of the financing structure is 0.725 with a standard deviation of 8.148, which means, on average, 72.5% of the debt is financed from the fixed assets of the financial listed firms of Pakistan quarterly. The minimum and maximum values of the financing structure are -118.247 and 90.947, respectively. The negative minimum value is because certain firms have more current assets than total liabilities, showing a conservative financing structure. The skewness and kurtosis values are -6.242 and 132.894 respectively, which shows that the spread and height of data for financing structure does not fall within the normal range. The Jarque-Bera statistics for financing structure have significant probability value, which shows that the data of financing structure is non-normal.

From the table 4.1, it can be observed that the mean size value is 10.256, with a standard deviation of 1.217. The minimum and maximum size values are 7.468 and 13.620, respectively. The values of skewness and kurtosis are 0.247 and 2.750, respectively, which shows that the spread and height of the data for size fall within the normal range. The Jarque-Bera statistics for size have a significant probability value, which shows that the data for size is non-normal.

The tabulated results suggest that the mean value of the consumer price index is 0.015 with a standard deviation of 0.007, which means, on average, 1.5% is the quarterly inflation rate in Pakistan from 2012 to 2019. The minimum and maximum values of the consumer price index are 0.005 and 0.034, respectively. The skewness and kurtosis values are 0.554 and 2.592 respectively, which shows that the spread and the height of data for consumer price index fall within the normal range. The Jarque-Bera statistics for the consumer price index have a significant probability value, which shows that the consumer price index data is non-normal.

Based on the table 4.1, the mean value of the interest rate is 0.022 with a standard deviation of 0.007, which means, on average, 2.2% is the quarterly rate of interest in Pakistan from 2012 to 2019. The minimum and maximum values of interest rate are 0.015 and 0.038, respectively. The skewness and kurtosis values are 0.642 and 2.942, respectively, which shows that the spread and the height of data for interest rate fall within the normal range. The Jarque-Bera statistics for the consumer price index have a significant probability value, showing that the interest rate data is non-normal.

The statistics in the table 4.1 confirm that the mean value of unemployment is 0.008 with a standard deviation of 0.002, which means, on average, 0.8% is the quarterly unemployment rate from Pakistan's total labour force from 2012 to 2019. The minimum and maximum values of unemployment are 0.002 and 0.010, respectively. The skewness and kurtosis values are -0.945 and 2.676 respectively, which shows that the spread and the height of data for unemployment fall within the normal range. The Jarque-Bera statistics for unemployment have a significant probability value, which shows that the unemployment data is non-normal.

As shown in the table 4.1, the mean volatility value is 0.020 with a standard deviation of 0.008, which means, on average, 2% is the quarterly volatility rate in Pakistan from 2012 to 2019. The minimum and maximum values of volatility are 0 and 0.217, respectively. The skewness and kurtosis values are 9.975 and 218.895 respectively, which shows that the spread and the height of data for volatility fall within the normal range. The Jarque-Bera statistics for volatility have a significant probability value, which shows that the volatility data is non-normal.

Our tests for skewness, kurtosis, and Jarque-Bera have revealed that the data does not follow a normal distribution. This significant finding underscores the necessity for additional tests, such as unit root, multicollinearity, autocorrelation, and heteroscedasticity, to validate the normality of the data. These tests are crucial in ensuring the accuracy and reliability of our analysis.

4.1.2 Diagnostic Testing of the Variables

The unit root test, a crucial step in our research, determines whether the variables under study are stationary. This research study uses Phillips–Perron and Augmented Dickey-Fuller tests to assess data stationarity (Bell et al., 2022). Although some variables such as inflation rate, and sales growth are already measured as percentage change; yet percentage changes reduce, but do not eliminate the risk of non-stationarity, and unit root testing remains a best practice to confirm the statistical properties of the data before proceeding with empirical analysis as done in the study of Kolawole et al. (2024). The results of these comprehensive unit root tests are meticulously detailed in the results table, which is reported in Table 4.2.

Table 4.2 shows the unit root test results of stock returns, share mispricing, gold bullion, consumer confidence index, turnover, advance-decline ratio, relative strength index, sales growth, financing structure, and unemployment are significant at a level for PP-Fisher and ADF-Fisher chi-square; thereby reporting stationarity at the level. The bond yield spread and size results are significant at the first difference, thereby reporting difference stationarity. However, the consumer price index and interest rate are significant at the second difference, reporting the second difference stationarity.

Table 4.2

Unit Root Test

	At level		At 1st Difference		At 2nd Difference	
	PP - Fisher Chi-square	ADF - Fisher Chi-square	PP - Fisher Chi-square	ADF - Fisher Chi-square	PP - Fisher Chi-square	ADF - Fisher Chi-square
R	806.587	393.777	1835.260	1008.350	1866.430	1321.140
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
SMP	949.455	516.63	1733.570	1006.210	2160.220	1297.340
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
BON	146.275	110.877	1069.960	599.221	2118.720	1456.710
(p-value)	0.001	0.176	0.000	0.000	0.000	0.000
GOLD	1127.170	404.332	1837.890	950.306	1882.490	1238.020
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
CCI	1480.110	486.603	1747.230	1015.800	1865	1191.690
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
TURN	324.735	303.036	1205.870	767.373	1819.400	1184.460
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
ADR	773.861	410.668	1358.990	1010.970	1991.040	1303.620
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
RSI	933.920	453.027	1556.580	1026.090	1916.280	1375.430
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
SALES	214.825	183.721	287.987	193.952	1112.460	488.466
(p-value)	0.000	0.000	0.000	0.000	0.000	0.000
FIN	131.963	140.603	221.066	156.851	1091.770	469.344
(p-value)	0.013	0.003	0.000	0.000	0.000	0.000
SIZ	125.856	71.0509	184.788	131.515	1077.810	458.523
(p-value)	0.031	0.982	0.000	0.014	0.000	0.000
CPI	47.735	31.605	98.577	43.495	1305.480	559.116
(p-value)	1.000	1.000	0.465	1.000	0.000	0.000
INT	31.472	19.8832	37.436	17.3741	1298.910	523.666
(p-value)	1.000	1.000	1.000	1.000	0.000	0.000
UNEMP	236.047	141.915	349.092	249.551	1351.160	563.787
(p-value)	0.000	0.003	0.000	0.000	0.000	0.000

4.1.3 Multicollinearity Test

In order to explore the relationship among variables, it is essential to find a correlation among them. The multicollinearity test results in the strength of the relationship among variables (with the value) and the direction of the relationship among variables (with the sign of value). The correlation coefficient value falls between -1 and 1, where -1 shows a perfect inverse relationship, 0 shows no relationship or statistical independence, and +1 shows a perfect direct relationship. If the absolute value exceeds 0.7, it reveals a strong correlation among variables. However, an absolute value of 0.5 to 0.7 reveals a substantial correlation among variables, and 0.3 to 0.5 reveals a moderate correlation. On the other hand, values ranging from 0.01 to 0.3 show a weak correlation (Gujarati & Porter, 2003). The correlation test of this study is described in the results table reported as Table 4.3.

Table 4.3 shows the result for the multicollinearity test in which there is a weak correlation between share mispricing and all other independent variables. In addition, there is a weak correlation between bond yield spread and all other independent variables except inflation (consumer price index) and interest rate, where inflation has a substantial strength of relationship and interest rate has a moderate strength of relationship with bond yield. In addition, there is a weak correlation between gold bullion and all other independent variables except the consumer confidence index, which has a moderate strength of relationship. Moreover, a weak correlation exists between the consumer confidence index and all other independent variables. Furthermore, a weak correlation exists between the consumer confidence index and all other independent variables. There is also a weak correlation between turnover and all other independent variables. There is a weak correlation between the advance-decline ratio and all other independent variables, except the relative strength index, which has a moderate strength of relationship with the advance-decline ratio.

Furthermore, there is a weak correlation between the relative strength index and all other independent variables. In addition, there is a weak correlation between sales, financing structure, size, unemployment, and volatility with all other independent variables. However, unemployment has a substantial correlation with the interest rate, and the interest rate has a substantial correlation with the inflation rate. The interest rate and inflation rate cause a substantial correlation, thereby revealing multicollinearity.

Table 4.3

Correlation Matrix

	R	SMP	BON	GOLD	CCI	TURN	ADR	RSI	SALES	FIN	SIZ	CPI	INT	UNEMP	VOL
R	1.000														
SMP	0.012	1.000													
BON	-0.044	0.008	1.000												
GOLD	-0.228	0.018	0.068	1.000											
CCI	0.077	0.004	0.062	-0.479	1.000										
TURN	0.092	-0.009	-0.019	-0.061	0.056	1.000									
ADR	0.632	0.005	-0.013	-0.101	0.064	0.028	1.000								
RSI	0.551	-0.011	-0.037	-0.081	-0.013	-0.009	0.474	1.000							
SALES	0.039	0.019	0.003	-0.014	0.028	0.219	-0.017	-0.023	1.000						
FIN	-0.015	0.001	-0.032	0.027	0.003	-0.098	-0.013	0.000	0.012	1.000					
SIZ	-0.095	0.040	-0.049	0.058	-0.035	0.191	-0.093	-0.044	0.059	0.079	1.000				
CPI	0.135	-0.021	-0.432	0.074	-0.108	0.073	0.098	0.087	-0.019	-0.033	-0.002	1.000			
INT	0.100	-0.031	-0.758	0.074	-0.096	0.063	0.066	0.053	0.003	-0.021	0.008	0.948	1.000		
UNEMP	-0.233	0.025	0.045	0.133	-0.113	-0.134	-0.168	-0.103	-0.048	-0.006	0.106	-0.586	-0.573	1.000	
VOL	0.024	0.030	-0.091	0.093	-0.035	0.121	0.042	-0.073	0.043	-0.015	-0.186	0.128	0.136	-0.055	1.000

The VIF test is calculated to further explore the multicollinearity among variables. It estimates how much the variation in regression coefficients varies if the model includes an independent variable compared to the model without the independent variables. The threshold value of VIF is 10, meaning the coefficients having a VIF of less than 10 are not correlated.

Table 4.4

Variance Inflation Factors

Variable	VIF
SMP	1.005
BON	1.426
GOLD	1.391
CCI	1.343
TURN	1.137
ADR	1.332
RSI	1.309
SALES	1.062
FIN	1.031
SIZ	1.088
CPI	10.683
INT	10.446
UNEMP	1.916

Table 4.4 shows the result for multicollinearity. In the VIF test, the value of all variables is less than 10 except the interest rate (10.446) and inflation rate (10.683). It surpass this threshold, suggesting a high degree of collinearity likely due to their inherent economic interdependence. To mitigate the impact of multicollinearity on the model's estimates, a systematic approach was adopted whereby these variables were excluded individually and jointly to evaluate their influence on multicollinearity and model stability. Upon sequential omission and re-estimation, the results demonstrated a reduction in VIF values and enhanced model robustness. Consequently, both inflation and interest rate were

excluded from the final regression analysis to ensure the integrity of coefficient estimates and to avoid multicollinearity-induced bias. This approach balances the need to control for macroeconomic factors with the imperative to maintain the statistical validity of the model, thereby strengthening the reliability of the empirical findings.

Ultimately, the decision to omit both inflation and interest rate variables in the final model is driven by empirical evidence from diagnostic tests and the need to maintain model parsimony and accuracy. The other remedies for multicollinearity are also considered, such as combining inflation and interest rates into a composite indicator, applying dimensionality reduction techniques like Principal Component Analysis (PCA), or using ridge regression methods. It is useful if the goal of this study was data reduction or constructing a composite sentiment index. Ridge regression's penalty can bias the parameter estimates, which is undesirable when the objective is to accurately estimate long-term economic relationships, as is the case in cointegration analysis.

4.1.4 Autocorrelation Test

After multicollinearity, the autocorrelation test is performed to check the correlation of the variables with their previous values. The autocorrelation problem may arise in time series and panel data. This study uses panel data, so the autocorrelation is checked before further analysis. For this purpose, the Durbin-Watson test is performed, and the threshold values fall between 0 and 4, where values closer to 2 show no autocorrelation (Saunders *et al*., 2021). The autocorrelation test of this study is described in the results table reported as Table 5. This table shows the result, which expresses the absence of autocorrelation since the statistics show a value of 1.940, closer to 2.

Table 4.5

Durbin Watson Test

Durbin-Watson stat	1.940

4.1.5 Heteroscedasticity Test

The heteroscedasticity test assesses how many errors are spread across observations. The likelihood ratio of the heteroscedasticity test is used in this study to assess that the residuals are homoscedastic (Saunders *et al*., 2021). The heteroscedasticity test of this study is described in the results table reported in Table 6. This table shows results that cross-sections and periods have a probability of less than 0.05, thereby reporting that residuals are heteroscedastic. However, this assumption is violated in panel regression due to its impracticability (Burdisso & Sangiácomo, 2016). Therefore, the presence of heteroscedasticity does not undermine the reliability of the results.

Table 4.6

Heteroscedasticity Test

Heteroscedasticity LR Test		
	Likelihood Ratio	Probability
Panel Cross-section	452.168	0.000
Panel Period	248.065	0.000

4.1.6 Endogeneity Test

The endogeneity test determines the endogenous or exogenous properties of model variables. Endogeneity is a correlation between independent variables and error terms, leading to inefficient and biased parametric estimates. The model has concerns about reverse causality or probable simultaneity in the case of endogenous variables. The significant probability (p-value > 0.05) of the Wald test states that variables are endogenous (Brooks, 2019). The endogeneity test of this study is described in the results table, which is reported in Table 4.7.

Table 4.7 shows results, which reveal that gold bullion, advance-decline ratio, relative strength index, turnover ratio, sales growth, size, and unemployment are endogenous as their p-value is less than 0.05. This shows that the model has a problem of endogeneity.

Table 4.7

Endogeneity Test

Wald Test	
Variable	Probability
SMP	0.274
BON	0.587
GOLD	0.000
ADR	0.000
CCI	0.063
RSI	0.000
TURN	0.002
FIN	0.873
SALES	0.050
SIZ	0.050
UNEMP	0.000

4.1.7 Cointegration Test

The cointegration is finding probable associations between the processes of time series data in the long run. The Engle-Granger is a test to identify the cointegrating relation between variables. It makes errors (residuals) based on static regression and uses errors to check the presence of unit root using the Augmented Dickey-Fuller Test. There is stationarity in residuals in the case of cointegration in the time series data. The null hypothesis of this test states that there is no cointegration. However, the alternate hypothesis of this test states that there is cointegration (Brooks, 2019). The cointegration test of this study is described in the results table, Table 4.8. The table shows results with a p-value less than 0.05 and t-statistics of -20.088, which rejects the null hypothesis. It reveals that there is a cointegration relationship between variables.

Table 4.8

Cointegration Test

Kao Residual Cointegration Test		
	t-Statistics	Probability
ADF	-20.088	0.000

4.2 Estimation of Models

4.2.1 Investor's Sentiment and Stock Returns

The hypotheses are set in chapter 2 of this research study to test the relation between investor sentiments' proxies and stock returns. The empirical testing of the hypotheses requires panel regression analysis based on equation 3.23 in section 3.13.2 of chapter 3.

The above diagnostic tests related to normality, unit root test, multicollinearity, heteroscedasticity, and endogeneity reveal that the data set is not parametric (Hair *et al*., 2019) and rather has non-parametric properties, therefore the non-parametric test is applied to test the hypotheses of this research study.

Endogeneity arises when explanatory variables are correlated with the error term, potentially due to omitted variable bias, simultaneity (e.g., investor sentiment and stock returns may influence each other) and measurement error. In the context of this study, investor sentiment proxies (e.g., share mispricing, bond yield spread, CCI) could be endogenous, as they are potentially influenced by past stock returns and other macroeconomic shocks. This bidirectional causality creates a theoretical basis for suspecting endogeneity. To empirically support the presence of endogeneity, a Wald test is applied. The test results indicates that the coefficients of the explanatory variables are jointly significant, and residuals were not orthogonal to regressors, confirming the presence of endogeneity and justifying the need for estimators that can handle it. Considering the evaluation techniques, the study considered more robust estimators: difference GMM and system GMM. Difference GMM is suitable for short panels (large N, small T), uses lagged levels as instruments for first differences. On the other hand, system GMM combines equations in levels and first differences to improve efficiency, particularly when variables are persistent. The panel in this study has moderate T (time periods) and moderate N (cross-sections), reducing the strength of GMM instruments. GMM requires a large number of valid instruments, and in moderate-sized panels, it risks instrument proliferation and weak instrument bias. FMOLS is suitable when the variables are cointegrated (which has been established in this study), there is heterogeneity across cross-sections, the objective is to obtain long-run equilibrium estimates, the panel is balanced with moderate N and T, and the focus is on correcting serial correlation and endogeneity in cointegrated regressions without over-reliance on instruments. FMOLS modifies OLS by using semi-parametric corrections to address endogeneity and serial correlation, making it a robust estimator in this context.

The FMOLS test is a cointegration test used if all variables have first difference stationarity and there is cointegrating relationship among variables (Agyemang & Bardai, 2022). To ensure the stationarity of stock returns, share mispricing, gold bullion, consumer confidence index, turnover, advance-decline ratio, relative strength index, sales growth, financing structure, and unemployment, a thorough data conversion process is undertaken, thereby reporting first difference unit root of all variables (I (1)) and meeting the criteria of the FMOLS test. In addition, the FMOLS model is used in this research study to test the hypotheses in order to deal with the concerns of heteroscedasticity and endogeneity (Brooks, 2019). Similar to Engel-Granger's technique, this model allows OLS to be used when there is long-term relationship (cointegration) between the dependent variable and its fundamentals (Brooks, 2019). The two-steps of Engel-Granger's technique cover the following steps (Brooks, 2019):

Table 4.9

Unit Root Test of Error term

ECT	Statistic	Prob.
ADF - Fisher Chi-square	1020.820	0.000

Table 4.9 shows the unit root of the error correction model, which is significant at 1 per cent with the ADF test at the level. Suppose all variables are stationary at the first

difference I (1), and the error term is stationary at the level I (0). In that case, cointegration exists, and there is a long-run relationship between variables (Brooks, 2019). The second step covers the estimation of the short run regression model using equation 3.23 and the results are as follows:

Table 4.10

Error Correction Mechanism

Dependent Variable: D(R)
Method: Panel Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SMP)	0.001	0.000	2.588	0.010
D(BON)	1.415	0.360	3.934	0.000
D(GOLD)	-0.312	0.028	-11.090	0.000
D(CCI)	-0.095	0.028	-3.416	0.001
D(TURN)	0.127	0.033	3.831	0.000
D(ADR)	0.240	0.008	28.485	0.000
D(RSI)	0.004	0.000	18.720	0.000
D(SALES)	0.070	0.034	2.095	0.036
D(FIN)	0.000	0.001	0.106	0.916
D(SIZ)	0.028	0.062	0.450	0.653
D(UNEMP)	-9.454	4.042	-2.339	0.020
ECT (-1)	-1.007	0.027	-37.975	0.000

Table 4.10 shows the error correction mechanism and the results that the coefficient of ECT (γ) is negative and significant (-1.007), which shows that the model adjusts itself in the long run (Brooks, 2019). Therefore, regression of the FMOLS model is tested for equation 3.23 and the results are presented in table 4.11.

Table 4.11

Panel Regression Results for Stock Returns

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SMP	0.002	0.001	2.277	0.023
BON	-0.789	0.318	-2.479	0.013
GOLD	-0.289	0.046	-6.233	0.000
CCI	-0.100	0.050	-2.019	0.044
TURN	0.085	0.032	2.622	0.009
ADR	0.231	0.012	19.935	0.000
RSI	0.004	0.000	14.366	0.000
SALES	0.045	0.020	2.234	0.026
FIN	0.000	0.001	0.652	0.515
SIZ	-0.052	0.017	-3.106	0.002
UNEMP	-5.504	2.201	-2.501	0.013
VOL	0.221	0.6465	0.342	0.732
R-squared			0.549	

The first hypothesis of this study is as under:

H_1: *There is a positive impact of share mispricing on the stock returns in the Pakistani Stock Market*

Table 4.11 depicts the results of the test to test the relation between share mispricing and stock returns. They reveal that the beta coefficient is positive (0.002) with a t-statistic of 2.277 (p-value 0.023). This implies that, controlling for all other variables in the model, a one-unit increase in share mispricing is associated with an average 0.002 unit increase in stock returns, holding other factors constant. It shows that there is a positively significant relation between share mispricing and stock returns in the Pakistani stock market at the 5% level of confidence, thereby accepting this hypothesis. This suggests that as mispricing (overvaluation) increases, returns increase, showing that sentiment-driven overpricing is rewarded in the sample period. Overvalued stocks may also generate returns in the short term due to speculative trading, particularly in sentiment-driven environments.

The second hypothesis of this study is as under:

H_2: *There is a negative impact of bond yield spread on the stock returns in the Pakistani stock market*

Table 4.11 depicts the results of testing the relation between bond yield spread and stock returns. This reveals that the beta coefficient is negative (-0.789) with a t-statistic of -2.479 (p-value 0.013). This implies that, controlling for other explanatory variables in the model, a one-unit increase in the bond yield spread is associated with an average 0.789 unit decrease in stock returns. It shows a negative significant relationship between bond yield spread and stock returns in the Pakistani stock market at a 5% confidence level, thereby allowing this hypothesis to be accepted. This implies that when the bond yield spread widens, typically interpreted as a sign of rising economic uncertainty or an expected downturn in economic activity, stock returns tend to decline.

The third hypothesis of this study is as under:

H_3: *There is a negative impact of gold bullion on the stock returns in the Pakistani stock market*

Table 4.11 depicts the results of testing the relation between gold bullion and stock returns. This reveals that the beta coefficient is negative (-0.289) with a t-statistics of -6.233 (p-value 0.000). This finding suggests that, holding other variables constant, a one-unit increase in gold bullion (as a sentiment proxy) is associated with an average 0.289 unit decline in stock returns. It shows a negative significant relationship between gold bullion and stock returns in the Pakistani stock market at a 1% level of confidence; thereby accepting this hypothesis. This means that when gold prices increase, stock returns tend to decline, and vice versa. This inverse relationship highlights the safe-haven nature of gold, particularly during times of market stress or economic uncertainty.

The fourth hypothesis of this study is as under:

H_4: *There is a negative impact of consumer confidence index on the stock returns in the Pakistani stock market*

Table 4.11 depicts the results of the test to test the relation between the consumer confidence index and stock returns. They reveal that the coefficient is negative (-0.100) with a t-statistic of -2.019 (p-value 0.044). This suggests that, controlling for other variables in the model, a one-unit increase in CCI is associated with a 0.100 unit decrease in stock returns on average. It shows a negative significant relationship between the consumer confidence index and stock returns in the Pakistani stock market at a 5% confidence level, thereby allowing this hypothesis to be accepted. This implies that as consumer confidence rises, stock returns tend to decline, and vice versa. Investors may interpret an overly high CCI as a signal of overheating in the economy, leading to expectations of monetary tightening, inflation control measures, or reduced future growth potential. As a result, investors may adopt a more cautious stance, reducing equity exposure and causing stock returns to decline in anticipation of macroeconomic corrections.

The fifth hypothesis of this study is as under:

H_5: *There is a positive impact of turnover on the stock returns in the Pakistani stock market*

The results, to test the relation between turnover and stock returns, are depicted in Table 4.11. They reveal that the beta coefficient is positive (0.085) with a t-statistic of 2.622 (p-value 0.009). This suggests that, controlling for other variables in the model, a one-unit increase in turnover is associated with an average increase of 0.085 units in stock returns. It shows a positively significant relation between turnover and stock returns in the Pakistani stock market at the 1% level of confidence, thereby accepting this hypothesis. A rise in turnover typically reflects increased investor attention, optimism, and confidence in the market or in particular stocks, leading to buying pressure and hence higher returns.

The sixth hypothesis of this study is as under:

H_6: *There is a positive impact of advance-decline ratio on the stock returns in the Pakistani stock market*

Table 4.11 depicts the results of the test to test the relation between the advance-decline ratio and stock returns. They reveal that the beta coefficient is positive (0.231) with a t-statistic of 19.935 (p-value 0.000). This implies that, holding other explanatory variables constant, a one-unit increase in the ADR is associated with a 0.231 unit increase in stock returns on average. It shows a positive relationship between the advance-decline ratio and stock returns in the Pakistani stock market at a 1% confidence level, thereby allowing the acceptance of this hypothesis. This suggests that as the number of advancing stocks outpaces the number of declining stocks, the overall stock returns tend to increase. A high ADR indicates broad-based participation in the market rally, suggesting widespread investor confidence and optimism. This collective bullish behaviour can drive the overall market index upward, resulting in positive stock returns.

The seventh hypothesis of this study is as under:

H_7: *There is a positive impact of relative strength index on the stock returns in the Pakistani stock market*

Table 4.11 depicts the results of testing the relationship between the relative strength index and stock returns. This reveals that the beta coefficient is positive (0.004) with a t-statistic of 14.366 (p-value 0.000). This suggests that, holding other variables constant, an increase in RSI is associated with a statistically significant rise in stock returns. It shows a positive relationship between the relative strength index and stock returns in the Pakistani stock market at a 1% confidence level, thereby allowing the acceptance of this hypothesis. An increasing RSI signals that a stock (or the market) has had strong recent price performance, which can attract more investor interest and further drive up prices, especially in markets where momentum trading is common.

4.2.2 Firm-Specific Fundamental Variables and Stock Returns

The results, to test the relation between sales growth and stock returns, are depicted in table 4.11, which reveal that the beta coefficient is positive (0.045) with the t-statistic of 2.234 (p-value 0.026). This suggests that, controlling for other explanatory variables, an increase in a firm's sales growth is associated with 0.045 unit increase in its stock returns. It shows that there is a positively significant relation between sales growth and stock returns in the Pakistani stock market at 5% level of confidence. This means that firms reporting higher growth in sales tend to experience higher stock returns, highlighting the relevance of firm-level fundamentals in influencing investor behaviour. This positive relationship suggests that investors reward companies that demonstrate improving top-line performance, interpreting it as a sign of strong business prospects, effective management, and competitive advantage. As expectations of future earnings increase with rising sales, investors may bid up the stock price, resulting in enhanced returns.

The results, to test the relation between financial structure and stock returns, are depicted in table 4.11, which reveal that the beta coefficient is positive (0.000) with the t-statistic of 0.652 (p-value 0.515). It shows a positively insignificant relation between financial structure and stock returns in the Pakistani stock market. Although the direction of the relationship is positive which implies that firms with stronger or more optimal financial structures might experience higher stock returns. However, the lack of statistical significance suggests that this relationship is not strong or consistent enough to be considered reliable within the sample studied. In other words, variations in financial structure do not significantly explain changes in stock returns in the Pakistani stock market, at least during the period and conditions analysed.

The results, to test the relation between firm size and stock returns, are depicted in table 4.11, which reveal that the beta coefficient is negative (-0.052) with the t-statistic of -3.106 (p-value 0.002). It shows a negatively significant relation between size and stock returns in the Pakistani stock market at 1% level of confidence. This result implies that smaller firms tend to generate higher stock returns compared to larger firms.

4.2.3 Macroeconomic Variables and Stock Returns

The diagnostic tests of multicollinearity in table 4.3 and 4.4 reveals that inflation has multicollinearity with other exogenous variables, therefore this variable is excluded from further analysis at first.

The diagnostic tests of multicollinearity in table 4.3 and 4.4 reveals that interest rate has multicollinearity with other exogenous variables, therefore this variable is excluded from further analysis at second step and results are improved. Therefore, inflation and interest rate are excluded from the analysis.

The results, to test the relation between unemployment and stock returns, are depicted in table 4.11, which reveal that the beta coefficient is negative (-5.504) with the t-statistic of -2.501 (p-value 0.002). It shows a negatively significant relationship between unemployment and stock returns in the Pakistani stock market at 1% level of confidence. Rising unemployment typically signals economic slowdown, reduced consumer spending, and weakened corporate earnings, which negatively affects investor confidence and stock valuations. This implies that, after controlling for other variables, higher unemployment is associated with lower stock returns in the Pakistani stock market.

4.2.4 Stock Return Volatility and Stock Returns

In order to test the relation of stock returns volatility when explanatory variables are incorporated, the hypothesis are set in chapter 2 of this research study. The examination of hypothesis is based on regression equation 3.23 in chapter 3.

The eighth hypothesis of this study is as under:

H_8: *The stock return volatility negatively impacts stock returns of the Pakistani stock market*

The results, to test the factors of investor sentiments in affecting stock returns volatility, are depicted in table 4.11, which reveal that the beta coefficient is positive (0.221) with the t-statistic of 0.342 (p-value 0.732). It shows that there is a positively insignificant relation between stock returns volatility and stock returns in the Pakistani stock market; thereby rejecting this hypothesis. This result indicates that although there appears to be a slight positive association between volatility and stock returns, the relationship is statistically insignificant, suggesting that volatility does not have a meaningful impact on stock returns in the Pakistani stock market within the observed period. This finding implies that, after accounting for other influencing variables, volatility does not significantly explain variations in stock returns.

The table 4.11 shows R square as 0.549 revealing 54.9% variation in the stock returns as explained by the exogenous variables of this research study.

4.2.5 Lead-Lag Relationship of Investor Sentiments and Stock Returns

4.2.5.1. Lag Length Selection Criteria.

In order to test the lead-lag relation of investor sentiments and stock returns, the lag order is required to capture the related history of model variables. VAR lag order selection criteria propose four methods for selecting lag orders (FPE, AIC, SC, and HQ), among which AIC and SC are considered superior (Brooks, 2019). The lag order selection criteria are made under the criterion as tested in Table 4.12, which shows that the seven lag orders are significant based on all criteria. Therefore, the lead-lag relation among investor sentiments and stock returns is tested with seven lags.

Table 4.12

Lag Order Selection Criteria

VAR Lag Order Selection Criteria						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-724.926	NA	0.000	1.335	1.371	1.349
1	828.139	3080.670	0.000	-1.377	-1.049	-1.253
2	1274.991	879.867	0.000	-2.075	-1.455	-1.840
3	1769.089	965.696	0.000	-2.858	-1.947	-2.513
4	2235.698	905.171	0.000	-3.591	-2.389	-3.136
5	3204.794	1865.818	0.000	-5.240	-3.746	-4.675
6	3850.675	1234.115	0.000	-6.300	-4.514	-5.624
7	7183.809	6320.206*	0.000*	-12.255*	-10.178*	-11.469*

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

4.2.5.2. Granger Causality Test

After selection of optimal lag length, the next step is to test the lead-lag relation among investor sentiments and stock returns and the test to detect such relation is Granger Causality Test (Brooks, 2019). In order to test the lead-lag relation of investor sentiments and stock returns, the hypotheses are set in chapter 2 of this research study. The ninth hypothesis of this study is as under:

H_9: *The investor sentiments have lead-lag relation with stock returns of the Pakistani stock market*

To examine the hypothesis that investor sentiments have a lead-lag relationship with stock returns in the Pakistani stock market, the Granger causality test is employed as the primary tool. This test determines whether past values of investor sentiment contain statistically significant information that can help predict future stock returns, thereby identifying the direction of causality or lead-lag relationships between the variables. Following this, the Vector AutoRegression (VAR) model is estimated to capture the dynamic interdependencies and feedback effects between investor sentiment and stock returns over time. While the VAR model analyzes the joint evolution of these variables, it does not explicitly establish causality direction; therefore, the Granger causality test is a necessary preliminary step to justify the model specification and interpret the directionality in the relationships. Together, these methods provide a comprehensive framework to investigate both the presence and dynamics of the lead-lag relationships between investor sentiment and stock returns in the Pakistani stock market.

The results of Granger Causality Test are presented in the results table reported as table 4.13. The pairwise Granger Causality Test shows 7 lags i.e. up to seven lags, a variable predicts another variables' value. The result of lead-lag relation between share mispricing and stock returns show that share mispricing Granger Cause stock returns as the p-value is less than 0.05 i.e. significant at 95% confidence interval. However, stock returns do not Granger Cause share mispricing as the p-value is more than 0.05. Therefore, there is unidirectional relation between share mispricing and stock returns in which share mispricing Granger Cause stock returns up to seven lags.

Table 4.13

Granger Causality Test

Pairwise Granger Causality Tests

Lags: 7

Null Hypothesis:	Obs	F-Statistic	Prob.
SMP does not Granger Cause R	1121	2.36794	0.021
R does not Granger Cause SMP		1.85241	0.074
SMP → R			
BON does not Granger Cause R	1136	12.2315	0.000
R does not Granger Cause BON		7.42045	0.000
BON ↔ R			
GOLD does not Granger Cause R	1136	14.8947	0.000
R does not Granger Cause GOLD		12.8223	0.000
GOLD ↔ R			
CCI does not Granger Cause R	1136	25.9926	0.000
R does not Granger Cause CCI		16.0659	0.000
CCI ↔ R			
TURN does not Granger Cause R	1136	2.03165	0.048
R does not Granger Cause TURN		2.7782	0.007
TURN ↔ R			
ADR does not Granger Cause R	1113	1.21745	0.290
R does not Granger Cause ADR		0.59974	0.757
Indecisive			
RSI does not Granger Cause R	1136	5.33249	0.000
R does not Granger Cause RSI		2.00184	0.052
RSI → R			

The result of lead-lag relation between bond yield spread and stock returns show that bond yield spread Granger Cause stock returns as the p-value is less than 0.05 i.e. significant at 95% confidence of interval. Similarly, stock returns also Granger Cause bond yield spread as the p-value is less than 0.05. Therefore, there is bidirectional relation between bond yield spread and stock returns in which both Granger Cause each other up to seven lags.

The results of lead-lag relation between gold bullion and stock returns show that gold bullion Granger Cause stock returns as the p-value is less than 0.05 i.e. significant at 95% confidence interval. Similarly, stock returns also Granger Cause gold bullion as the p-value is less than 0.05. Therefore, there is bidirectional relation between gold bullion and stock returns in which both Granger Cause each other up to seven lags.

The results of lead-lag relation between consumer confidence index and stock returns show that consumer confidence index Granger Cause stock returns as the p-value is less than 0.05 i.e. significant at 95% confidence of interval. Similarly, stock returns also Granger Cause consumer confidence index as the p-value is less than 0.05. Therefore, there is bidirectional relation between consumer confidence index and stock returns in which both Granger Cause each other up to seven lags.

The results of lead-lag relation between turnover and stock returns show that turnover Granger Cause stock returns as the p-value is less than 0.05 i.e. significant at 95% confidence of interval. Similarly, stock returns also Granger Cause turnover as the p-value is less than 0.05. Therefore, there is bidirectional relation between turnover and stock returns in which both Granger Cause each other up to seven lags.

The results of lead-lag relation between advance-decline ratio and stock returns show that advance-decline ratio do not Granger Cause stock returns as the p-value is more than 0.05 i.e. insignificant at 95% confidence of interval. Similarly, stock returns also do not Granger Cause advance-decline ratio as the p-value is more than 0.05. Therefore, there no relation between advance-decline ratio and stock returns in which both Granger Cause each other up to seven lags.

The results of lead-lag relation between relative strength index and stock returns show that relative strength index Granger Cause stock returns as the p-value is less than 0.05 i.e. significant at 95% confidence of interval. However, stock returns do not Granger Cause relative strength index as the p-value is more than 0.05. Therefore, there is unidirectional relation between relative strength index and stock returns in which both Granger Cause each other up to seven lags.

Overall, the results show that bond yield spread, gold bullion, consumer confidence index, and turnover have presence of bi-directional lead-lag relation with stock returns in the Pakistani market throughout 2012-2019. The results further show that share mispricing and relative strength index have a unidirectional lead-lag relation with stock returns in the Pakistani market during the same period. On the other hand, the advance-decline ratio and stock returns have no lag relation in the Pakistani market from 2012 to 2019.

4.2.5.3. Vector Autoregressive Model

Once lag order is selected i.e., 7, as shown in Table 4.12, the next step is to assess the interdependencies of multiple variables. Granger causality is a preliminary diagnostic tool that tests whether one time series can predict another. It is often used to justify the inclusion of variables in a Vector AutoRegression (VAR) model by showing potential predictive relationships. The VAR test is applied for up to seven lag orders, and the estimates are presented in Table 4.14, as:

Table 4.14

Vector Autoregressive Model

Dependent Variable: R		
	Coefficient	t-statistic
R(-1)	0.044	1.060
R(-2)	0.051	1.252
R(-3)	0.007	0.177
R(-4)	0.012	0.307
R(-5)	-0.008	-0.189

R(-6)	0.056	1.417
R(-7)	-0.006	-0.170
SMP(-1)	-0.002	-2.579***
SMP(-2)	0.001	0.926
SMP(-3)	0.000	-0.214
SMP(-4)	-0.001	-1.516
SMP(-5)	-0.001	-0.932
SMP(-6)	-0.002	-1.881*
SMP(-7)	0.000	-0.204
BON(-1)	1.997	0.890
BON(-2)	-7.546	-6.332***
BON(-3)	0.140	0.111
BON(-4)	-2.906	-1.883*
BON(-5)	6.455	3.063***
BON(-6)	-5.770	-4.644***
BON(-7)	-1.280	-0.755
GOLD(-1)	0.753	3.137***
GOLD(-2)	-0.068	-0.541
GOLD(-3)	-0.481	-4.187***
GOLD(-4)	0.060	0.573
GOLD(-5)	0.052	0.378
GOLD(-6)	0.054	0.212
GOLD(-7)	-0.431	-2.792***
CCI(-1)	0.382	2.932***
CCI(-2)	0.028	0.169
CCI(-3)	-0.351	-1.615
CCI(-4)	0.805	4.825***
CCI(-5)	2.035	6.074***
CCI(-6)	0.828	2.882***
CCI(-7)	0.099	0.431
TURN(-1)	-0.024	-0.429

TURN(-2)	0.043	0.671
TURN(-3)	-0.049	-0.786
TURN(-4)	0.031	0.504
TURN(-5)	-0.149	-2.458**
TURN(-6)	0.003	0.055
TURN(-7)	0.112	2.470**
ADR(-1)	-0.030	-1.304
ADR(-2)	-0.017	-0.751
ADR(-3)	-0.020	-0.914
ADR(-4)	0.031	1.526
ADR(-5)	-0.005	-0.239
ADR(-6)	-0.042	-2.197**
ADR(-7)	0.009	0.510
RSI(-1)	0.000	-0.338
RSI(-2)	0.001	1.679*
RSI(-3)	0.001	1.857*
RSI(-4)	0.000	-0.771
RSI(-5)	0.000	-0.872
RSI(-6)	0.000	-0.946
RSI(-7)	-0.001	-1.758*
C	0.215	1.583

Where, * = significance at 10%, ** = significance at 5%, *** = significance at 1

The results of the VAR model show that stock returns do not show any interdependency with its lags. However, it shows the relation between stock returns and proxies of investor sentiments with different lags. SMP (-1) has a beta coefficient (-0.002) with a t-statistic of -2.579 (1% level of significance), which shows that the first lag of share mispricing has significant and negative relation with stock returns at a 1% level of significance. Moreover, SMP (-6) has a beta coefficient (-0.002) with a t-statistic of –1.881 (10% level of significance), which shows that the sixth lag of share mispricing has a significant and negative relation with stock returns at a 10% level of significance. However, there is no lag relation between SMP (-2) and stock returns, SMP (-3) and stock returns, SMP (-4) and stock returns, SMP (-5) and stock returns, and SMP (-7) and stock returns. The results of the VAR model reveal that while stock returns do not exhibit significant interdependence with their own lags, they do respond dynamically to past values of investor sentiment proxies. Specifically, share mispricing (SMP) at lag 1 and lag 6 demonstrates a statistically significant and negative effect on stock returns, indicating that changes in investor sentiment can influence market performance over both short-term and longer-term horizons. These findings suggest that investor sentiment exerts a lagged and time-dependent influence on stock returns. Although not all lags of SMP are significant, the VAR framework captures this relationship by considering the joint evolution of the variables across multiple periods, thus reflecting the dynamic interaction between them. The system of equations in the VAR model allows us to observe how shocks to investor sentiment at different points in time propagate through the system and affect stock return behaviour, reinforcing the lead-lag hypothesis.

The VAR estimates further show that BON (-2) has a beta coefficient (-7.546) with a t-statistic of -6.332 (1% level of significance), which shows that the second lag of bond yield spread has a significant and negative relation with stock returns at 1% level of significance. Furthermore, BON (-4) has a beta coefficient (-2.906) with a t-statistic of -1.883 (10% level of significance), which shows that the fourth lag of bond yield spread has a significant and negative relation with stock returns at a 10% level of significance. Moreover, BON (-5) has a beta coefficient (6.455) with a t-statistic of 3.063 (1% level of significance), which shows that the fifth lag of bond yield spread has a significant yet positive relation with stock returns at a 1% level of significance. In addition, BON (-6) has a beta coefficient (-5.770) with a t-statistic of -4.644 (1% level of significance), which shows that the sixth lag of bond yield spread has a significant and negative relation with stock returns at 1% level of significance. However, there is no lag relation between BON (-1) and stock returns, BON (-3) and stock returns and BON (-7) and stock returns. These results indicate that investor sentiment proxied by bond market behaviour affects stock returns in a complex, time-distributed manner. This pattern of alternating effects over several lag periods demonstrates a dynamic interaction between bond yield spread and stock returns, consistent with the premise of the VAR model. Rather than capturing a static or immediate relationship, the VAR framework enables the identification of lead-lag dynamics and the cumulative impact of past sentiment shocks on stock return behaviour. Thus, the results reflect how sentiment-related variables influence financial markets through evolving and time-dependent mechanisms, supporting the presence of a meaningful intertemporal relationship.

The VAR estimates further show that GOLD (-1) has a beta coefficient (0.753) with a t-statistic of 3.137 (1% level of significance), which shows that the first lag of gold bullion has a significant and positive relation with stock returns at 1% level of significance. Furthermore, GOLD (-3) has a beta coefficient (-0.481) with a t-statistic of -4.187 (1% level of significance), which shows that the third lag of gold bullion has a significant and negative relation with stock returns at a 1% level of significance. Moreover, GOLD (-7) has a beta coefficient (-0.431) with a t-statistic of -2.792 (1% level of significance), which shows that the seventh lag of gold bullion has a significant and negative relation with stock returns at a 1% level of significance. However, there is no lag relation between GOLD (-2) and stock returns, GOLD (-4) and stock returns, GOLD (-5) and stock returns and GOLD (-6) and stock returns. These findings demonstrate that the influence of gold sentiment on the stock market is not static, but unfolds over multiple time horizons with changing intensity and direction. The VAR model captures this intertemporal interaction, highlighting the lead-lag dynamics between gold-based investor sentiment and market performance. This dynamic evolution supports the broader hypothesis of sentiment-driven fluctuations in stock returns and illustrates how investors may react to macro-financial indicators like gold with both immediate and delayed behavioural responses.

The VAR estimates further show that CCI (-1) has a beta coefficient (0.382) with a t-statistic of 2.932 (1% level of significance), which shows that the first lag of consumer confidence has a significant and positive relation with stock returns at 1% level of significance. In addition, CCI (-4) has a beta coefficient (0.805) with a t-statistic of 4.825 (1% level of significance), which shows that the fourth lag of consumer confidence has a significant and positive relation with stock returns at a 1% level of significance. Furthermore, CCI (-5) has a beta coefficient (2.035) with a t-statistic of 6.074 (1% level of significance), which shows that the fifth lag of consumer confidence has a significant and positive relation with stock returns at a 1% level of significance. Moreover, CCI (-6) has a beta coefficient (0.828) with a t-statistic of 2.882 (1% level of significance), which shows that the sixth lag of consumer confidence has a significant and positive relation with stock returns at a 1% level of significance. However, there is no lag relation between CCI (-2) and stock returns, CCI (-3) and stock returns, and CCI (-7) and stock returns. This pattern indicates a persistent and reinforcing effect of consumer sentiment on market performance, whereby rising confidence among consumers correlates with improved stock returns across a sustained period. These results reflect the dynamic interaction between sentiment and stock returns, as captured by the VAR model. The system-wide analysis underscores that stock returns are not only affected by immediate changes in sentiment but also respond to accumulated perceptions and expectations formed over prior periods. The consistently positive direction of the effect highlights a stable link between macroeconomic optimism and equity market behaviour, supporting the view that consumer sentiment plays a meaningful role in driving return dynamics over time.

The VAR estimates further show that TURN (-5) has a beta coefficient (-0.149) with a t-statistic of –2.458 (5% level of significance), which shows that the fifth lag of share turnover has significant and negative relation with stock returns at 5% level of significance. Additionally, TURN (-7) has a beta coefficient (0.112) with a t-statistic of 2.470 (5% level of significance), which shows that the seventh lag of share turnover has a significant and negative relation with stock returns at a 5% level of significance. However, there is no lag relation between TURN (-1) and stock returns, TURN (-2) and stock returns, TURN (-3) and stock returns, TURN (-4) and stock returns, and TURN (-6) and stock returns. This mixed pattern of effects across time lags demonstrates the dynamic interaction between trading-based sentiment and market performance. The VAR model captures how fluctuations in investor activity influence returns not immediately, but through a staggered and evolving process, revealing both short-term corrections and longer-term sentiment alignment. These results support the broader hypothesis that trading intensity, as a reflection of market sentiment, contributes to return dynamics through complex lead-lag mechanisms.

The VAR estimates further show that ADR (-6) has a beta coefficient (-0.042) with a t-statistic of –2.197 (5% level of significance), which shows that the sixth lag of advance-decline ratio has significant and negative relation with stock returns at 5% level of significance. However, there is no lag relation between ADR (-1) and stock returns, ADR (-2) and stock returns, ADR (-3) and stock returns, ADR (-4) and stock returns, ADR (-5) and stock returns, and ADR (-7) and stock returns. This finding suggests that broader market weakness or declining breadth, observed six periods prior, negatively influences current stock returns. No significant lag relationships were found between ADR and stock returns at other lags. This result reflects a delayed sentiment effect, where a prior deterioration in market breadth exerts a measurable impact on future returns. The inclusion of ADR in the VAR framework supports the view that underlying market sentiment captured through breadth indicators contributes to the intertemporal evolution of stock returns, reinforcing the system-wide dynamics captured by the VAR model.

The VAR estimates further show that RSI (-2) has a beta coefficient (0.001) with a t-statistic of 1.679 (10% level of significance), which shows that the second lag of relative strength index has a significant and positive relation with the stock returns at a 10% level of significance. Furthermore, RSI (-3) has a beta coefficient (0.001) with a t-statistic of 1.857 (10% level of significance), which shows that the third lag of the relative strength index has a significant and positive relation with stock returns at a 10% level of significance. Additionally, RSI (-7) has a beta coefficient (-0.001) with a t-statistic of -1.758 (10% level of significance), which shows that the seventh lag of the relative strength index has significant and negative relation with stock returns at a 10% level of significance. However, there is no lag relation between RSI (-1) and stock returns, RSI (-4) and stock returns, RSI (-5) and stock returns, and RSI (-6) and stock returns. These findings reflect a nonlinear and time-varying sentiment-return relationship, where the influence of technical sentiment is contingent on the timing and nature of prior price strength. Within the VAR framework, RSI contributes to capturing how short-term momentum and long-term mean reversion jointly shape return dynamics. The presence of significant lags highlights RSI's role in the temporal evolution of market behaviour, reinforcing its function as a sentiment proxy in explaining return variation.

4.3 Robust Analysis

In order to analyse the robustness of results, this research study carried out robust analysis by using the omitted variables i.e. consumer price index and interest rate. These two variables are found to have strong correlation with bond yield spread. Therefore, two tests are run with each omitted variable i.e. consumer price index and interest rate and excluding bond yield spread as shown in table 4.15.

The results are reported in table 4.15 when consumer price index is used in the model in place of bond yield spread, which show that share mispricing has a coefficient of 0.002 (t-value = 2.390), gold bullion has a coefficient of -0.311 (t-value = -6.713), consumer confidence index has a coefficient of -0.106 (t-value = -2.078), turnover has a coefficient of 0.097 (t-value = 2.932), advance-decline ratio has coefficient of 0.229 (t-value = 19.468), relative strength index has coefficient of 0.004 (t-value = 14.071), sales growth has coefficient of 0.045 (t-value = 2.182), financing structure has coefficient of 0.000 (t-value = 0.764), and size has coefficient of -0.050 (t-value = -2.919); thus confirming that the results of these variables are consistent with the previous results. However, unemployment has coefficient of -2.477 (t-value = -0.877) when consumer price index is used in the model. The result of this variable is not conformed to previous results i.e. there is an insignificant and negative relationship between unemployment and stock returns in the Pakistani stock market. Furthermore, consumer price index has coefficient of 410.929 (t-value = 1.331); thus showing insignificant relation of consumer price index and stock returns. Therefore, it was better to omit this variable from the results of this research study.

Table 4.15

Robust Analysis

Dependent Variable: R

Variable	With CPI (without BOND)	With INT (without BOND)
SMP	0.002	0.002
	2.390**	2.375**
GOLD	-0.311	-0.304
	-6.713***	-6.576***
CCI	-0.106	-0.107
	-2.078**	-2.120**
TURN	0.097	0.098
	2.932***	2.953***
ADR	0.229	0.229
	19.468***	19.575***
RSI	0.004	0.004
	14.071***	14.134***
SALES	0.045	0.043
	2.182**	2.123**
FIN	0.000	0.000
	0.764	0.714
SIZ	-0.050	-0.045
	-2.919***	-2.572***
CPI	410.929	
	1.331	
INT		1.370
		1.602
UNEMP	-2.477	-2.145
	-0.877	-0.737
R-squared	0.551	0.550

***p < 0.01, **p < 0.05, *p < 0.1.

When interest rate is used in the model in place of bond yield spread, it shows that share mispricing has coefficient of 0.002 (t-value = 2.375), gold bullion has coefficient of -0.304 (t-value = -6.576), consumer confidence index has coefficient of -0.107 (t-value = -2.120), turnover has coefficient of 0.098 (t-value = 2.953), advance-decline ratio has coefficient of 0.229 (t-value = 19.575), relative strength index has coefficient of 0.004 (t-value = 14.134), sales growth has coefficient of 0.043 (t-value = 2.123), financing structure has coefficient of 0.000 (t-value = 0.714), size has coefficient of -0.045 (t-value = -2.572); thus confirming that the results of these variables are consistent with the previous results. However, unemployment has coefficient of -2.145 (t-value = -0.737) when interest rate is used in the model. The result of this variable is not conformed to the previous results i.e. there is an insignificant and negative relationship between unemployment and stock returns in the Pakistani stock market. Interest rate has coefficient of 1.370 (t-value = 1.602); thus showing insignificant relation of interest rate and stock returns. Therefore, it was better to omit this variable from the results of this research study.

The robustness of results is tested by using models with consumer price index and interest rate after excluding bond yield spread. The results show same significant results for share mispricing, gold bullion, consumer confidence index, turnover, advance-decline ratio, relative strength index, sales growth, and size. The results show same insignificant result for financing structure in both models. However, the unemployment becomes insignificant in both the robustness models. Therefore, it can be said that results of this research study are by and large robust with only one exception. The table 4.15 shows R square as 0.55 revealing 55% variation in the stock returns as explained by the exogenous variables of this research study. This value is also very close to the value of the original model; thus confirming the appropriateness of the robustness analysis.

In summary, this research study aims to test the relationship between investor sentiment proxies and stock returns in the Pakistani stock market. The study uses a non-parametric FMOLS model to examine investor's sentiments hypotheses. The results show a significant positive relation between share mispricing and stock returns, a significant negative relation between bond yield spread and stock returns, a significant negative relation between gold bullion and stock returns, and a significant negative relation between the consumer confidence index and stock returns. In contrast, turnover, advance-decline ratio, and relative strength index positively affect stock returns. Based on the analysis, all hypotheses are accepted at their respective confidence levels. This study also investigates the relationship between firm-specific fundamental variables and stock returns in the Pakistani stock market. It confirms a significant, positive relation between sales growth and stock returns, an insignificant relation between financial structure and stock returns, and a significant, negative relation between size and stock returns. The text also discusses examining hypotheses regarding the relation between macroeconomic variables and stock returns in the Pakistani stock market.

Inflation and interest rates were found to be multicollinear with other variables and were excluded from further analysis. A significant, negative relationship between unemployment and stock returns confirms the hypothesis. The hypothesis tested in this research study also examines the relationship between stock return volatility and investor sentiments in the Pakistani stock market. The results show an insignificant relation between volatility and stock returns, suggesting that investor sentiments do not significantly impact stock return volatility. The positive coefficient indicates a positive relation between stock returns volatility and stock returns.

This study also investigates the lead-lag relation of investor sentiments with stock returns in the Pakistani stock market. It confirms that bond yield spread, gold bullion, consumer confidence index, and turnover have a bi-directional lead-lag relation with stock returns. However, share mispricing and relative strength index have a unidirectional lead-lag relation with stock returns. On the other hand, the advance-decline ratio and stock returns have an indecisive lead-lag relationship. The overall results of the VAR model reveal a complex and dynamic interaction between investor sentiment proxies and stock returns in the Pakistani stock market. Multiple proxies exhibit significant lagged effects on returns, with varying directions and time horizons. For instance, SMP and BON show predominantly negative effects across specific lags, suggesting that mispricing and credit market signals can foreshadow corrections in equity prices. In contrast, positive and persistent effects of CCI across several lags underscore the reinforcing role of macroeconomic optimism in driving return dynamics. GOLD and RSI reveal mixed patterns, highlighting both safe-haven responses and momentum-driven behaviour, while TURN and ADR reflect the influence of trading intensity and market breadth through nonlinear lead-lag structures. These findings confirm that investor sentiment, as captured through diverse market-based indicators, significantly influences stock returns not instantaneously but through intertemporal feedback mechanisms. The VAR framework thus provides robust evidence of the temporal causality and evolving influence of sentiment on market performance, supporting the broader hypothesis of a lead-lag relationship between investor sentiment and stock returns. Therefore, it partially confirms this hypothesis, too.

Lastly, the robustness of results is tested first by using a model with a consumer price index excluding bond yield spread. The result reaps the same results for all variables except unemployment. Secondly, the robustness of the results is tested using a model with interest rate excluding bond yield spread. The result reaps the same results for all variables except unemployment. Therefore, the results of this research study are robust.

CHAPTER 5

DISCUSSION AND ANALYSIS

This chapter presents the discussion and analysis of the results and findings extracted in the previous chapter in the framework of theoretical and empirical research on the subject matter. This chapter aims to answer the research questions and objectives proposed in the first chapter of the thesis. The results show a significant impact of investor sentiments on the stock returns in the Pakistani Stock Market as shown in section 4.2 of the report, thereby directly addressing the research objectives. The research hypotheses accepted or rejected in the previous chapter are discussed and concluded in light of the historical research studies on the subject matter. In order to address and answer the results of research objectives and research questions in Chapter 1 of this report, this chapter is framed to give meaningful interpretations to the results extracted in Chapter 4.

Research objective 1 and research question 1, as shown in sections 1.3 and 1.4 of the report, are related to proxies of investor sentiments and their impact on stock returns. There are seven investor sentiment proxies (share mispricing, bond yield spread, gold bullion, consumer confidence index, share turnover, advance-decline ratio and relative strength index) used in this study and their impact on the stock returns is analysed as follows:

Share mispricing as a proxy of investor sentiments has a significant positive impact on stock returns in the Pakistani stock market, as shown in section 4.2.1 of the results chapter. The findings support the study of Chang *et al*. (2007) in which investor sentiments in the Australian capital market significantly impact stock returns. This relationship highlights the susceptibility of investors in Pakistan to sentiment-driven biases similar to those observed in more developed markets. The results also support the empirical research of Hwang *et al*. (2013), in which the investors tend to be influenced by biases (Reis & Pinho, 2021; Wu *et al*., 2018). The results negate the presence of an efficient market hypothesis in the real world and that investors are subject to be inclined from overconfidence bias and herd behaviour consistent with the theory discussed in sections 2.1.8.1 and 2.1.8.2 of the report, respectively. In a developing economy like Pakistan, these behavioural biases can be even more pronounced. Investors in such markets may lack access to comprehensive market information and advanced analytical tools, making them more prone to herd behaviour and overconfidence. The research studies find that investors are overly optimistic about the prospects of a specific firm, directing them to overvalue its stock and raise the share price even more than its fundamental worth (Bouteska & Regaieg, 2020; Iacurci, 2023; Wu *et al*., 2018). Mispricing in stock due to over-optimism positively impacts stock returns, which is consistent with the results of an under-considered study. Even though, the dynamics of this mispricing are considered short-term due to herd behaviour or overreaction. The market tends to correct itself by incorporating new information into the stock price over a long period. However, literature studies contradict that when the expectation about a firm price persists, then the investors follow the optimism for an extended period, thereby prevailing mispricing in the long run based on biased beliefs without any correction (Barberis & Thaler, 2003; Brown & Cliff, 2004; Huang *et al*., 2015). In this way, share mispricing has a positive impact on stock returns for a long period of time.

The bond yield spread as a proxy of investor sentiment significantly negatively impacts the stock returns in the Pakistani Stock market, as shown in section 4.2.1 of the results chapter. This result implies that bond yield spread is inverse to stock returns. It shows that when investors have low sentiments, they become risk-averse and find some alternate and safe assets, such as government bonds or corporate bonds, to encounter low default risk. This result is confirmed in the literature studies (Engstrom & Sharpe, 2019; Georgoutsos & Migiakis, 2013; Gómez-Puig *et al*., 2014). In this way, the negative sign for the bond yield curve is expected for sentiment changes. The same may hold for a higher level of sentiments, which suggests that investors' optimism puts less demand for debt securities, thereby increasing stock prices and decreasing bond yield, consistent with the study of Spyrou (2013). In a developing economy like Pakistan, investors' shift towards bonds during periods of low sentiment highlights their risk aversion in the face of economic uncertainty. This shift away from equities to bonds increases the demand for debt securities, leading to a decrease in stock prices and a corresponding increase in bond yields.

Conversely, during periods of high sentiment, investor optimism reduces the demand for bonds, driving up stock prices and lowering bond yields. The adverse quarterly changes in investor sentiments show an increased level of pessimism about the macroeconomic viewpoint, and an expectation of high uncertainty leads to high risk and high yield, conforming to the expectations theory explained in section 2.1.2 of the report. These results are similar to the findings of Baumeister (2021); Begum (2020) and Hamburger and Platt (1975). Other than country-related factors, investor sentiments played an influential role, especially in crises and crashes, in the effectiveness of interventions in the monetary policy, which is consistent with the study of Spyrou (2013). Monetary policies can intervene and help solve the crisis led by the illiquid market situation, primarily caused by increased confidence loss and risk aversion among investors. Giordano *et al*. (2012) find that the fiscal variables of high-debt economies are under-priced before and during financial turmoil. A positive sentiment helps lessen the spread of government bonds and vice versa, which can risk the economies (De Grauwe & Ji, 2013). Therefore, market sentiments majorly drive the yield spread (Favero & Missale, 2012); thereby impacting stock returns. In developing markets like Pakistan, where economic conditions are more volatile and investor information may be less complete, the influence of sentiment on yield spreads and stock returns can be even more pronounced. This underscores the importance of understanding and monitoring investor sentiment to better navigate the dynamics of stock and bond markets in developing economies.

Gold bullion as a proxy of investor sentiment has a significant negative impact on the stock returns in the Pakistani Stock market, as shown in section 4.2.1 of the results chapter. Gold serves as both an insurance policy and safe haven for major stock markets, potentially providing stability to the financial system by detecting losses ahead of severe adverse market shocks (Baur & McDermott, 2010). In this study, gold demonstrates a remarkable significance level of 1% across all estimations. However, the negative relation shows that gold is used as a hedge in the PSX since investors use it during adverse shocks in stock returns to compensate for loss, consistent with the study of Baur and Lucey (2010). Being a safe haven, gold has the property of a negative correlation with stock returns in case of stock market turmoil. In a developing economy like Pakistan, where economic and financial systems are often more volatile and susceptible to external shocks, the role of gold becomes even more critical. Investors in developing markets such as Pakistan may have limited access to sophisticated financial instruments and market information, making them more reliant on traditional safe haven assets like gold. This result is consistent with the theory of mental accounting, as mentioned in section 2.1.3 of the report. The preference for gold as a hedge in the PSX reflects the broader economic context of Pakistan. The country's developing status often entails higher economic uncertainty, inflation rates, and currency fluctuations, all of which can undermine investor confidence in the stock market. During such periods of economic instability, gold's negative correlation with stock returns becomes particularly valuable, offering a safeguard for investors' portfolios. This behaviour aligns with empirical studies (Baur & Lucey, 2010; Hood & Malik, 2013), which confirm gold's role as a hedge and a haven for stock market investors. It shows that the price of gold increases after a decrease in stock price and compensation for investors for their losses incurred with stock investments, consistent with the loss aversion theory mentioned in section 2.1.8.2 of the report. Therefore, gold serves as a hedge and haven for stock market investors in, consistent with the empirical studies (Baur & Lucey, 2010; El Hedi Arouri *et al*., 2015; Hood & Malik, 2013).

The consumer confidence index as a proxy of investor sentiment has a significant negative impact on the stock returns in the Pakistani Stock market, as shown in section 4.2.1 of the results chapter. The consumer confidence index is an impactful sentiment survey indicator (Simoes, 2011). Interestingly, the connection between the consumer confidence index, economic sentiment indicator, and capital market is only sometimes clear-cut in the literature. Instead, cultural elements play a significant role in moulding how optimism and pessimism circulate among economic players. A striking majority of research, consistent with this study, has revealed an inverse relationship between investor sentiments and stock returns – high investor sentiment often paves the way for low future returns. Therefore, consumer confidence measurements have been extensively utilized as reliable substitutes for investor sentiment (Jansen & Nahuis, 2003; Fisher & Statman, 2003; Lemmon & Portniaguina, 2006; Chui, Titman, & Wei, 2010). These researchers suggest two reasons for their results. The first can be explained by the traditional wealth effect, which demonstrates that stock prices affect investors' current wealth, affecting their confidence. The wealth effect only applies to consumers with direct investments in the stock exchange. The second reason can be explained by the leading indicator channel denoting that the current changes in stock prices affect future income and consumer confidence, as explained in the study of Bolaman and Evrim Mandacı (2014). When considering the context of Pakistan, a developing economy, several additional factors come into play. Developing economies often exhibit different market dynamics compared to developed markets, influenced by factors such as market maturity, investor behaviour, and economic stability. In Pakistan, market participants might react more sensitively to changes in consumer confidence due to the relatively lower levels of market sophistication and higher volatility. Furthermore, the cultural aspects specific to Pakistan could amplify the impact of consumer sentiment on stock returns. In developing economies, information asymmetry and market inefficiencies are more prevalent, leading to more pronounced reactions to sentiment indicators. Investors in Pakistan may rely more heavily on sentiment surveys like the consumer confidence index due to the lack of comprehensive and reliable market information. Moreover, economic conditions in developing economies like Pakistan are often more volatile, with higher exposure to political instability, inflation, and external shocks. These factors can significantly influence consumer confidence and, subsequently, investor sentiment. The interplay between these elements can lead to a more substantial inverse relationship between consumer confidence and stock returns in Pakistan compared to more stable and developed markets.

The turnover as a proxy of investor sentiment has a significant positive impact on the stock returns in the Pakistani Stock market, as shown in section 4.2.1 of the results chapter. The direct relation of the turnover rate (as a sentiment) on the stock returns is confirmed in several studies including Baker & Wurgler (2006), Baker & Wurgler (2007), Chen, Chong, & Duan (2010), Baker, Wurgler, & Yuan (2012), Huang, Jiang, Tu, & Zhou (2015), Yang & Zhou (2015, 2016), Kumari & Mahakud (2015), Asem, Chung, Cui, & Tian (2016), Jitmaneeroj (2017), Gao & Yang (2017), Ma, Xiao, & Ma (2018), Seok, Cho, & Ryu (2019), & Zhou (2018). The turnover indicates the level and effect of optimism in the business world. This information can help firms determine their level of liquidity and competitiveness. In this study's model, turnover impacts the stock return significantly with a predicting power of $\alpha = 1\%$. Baker and Stein (2004) confirm that liquidity, specifically the turnover, represents a sentiment index consistent with the investor sentiments theory, as explained in section 2.1.1 of the report. Baker and Wurgler (2007) also confirmed that low turnover shows that the behaviour of investors is a pessimist and vice versa. Whether the behaviour of an investor is optimistic or pessimistic, it impacts the stock's liquidity (Chen *et al*., 2020) in the same way as the turnover. This research result reveals that a high level of trading volume or market liquidity has been deemed as a sign of a stock's overvaluation, consistent with the study of Baker and Stein, (2004). If there are constraints with short-selling in any market, then only optimistic retail investors participate in it, increasing the volume of trade. Therefore, in optimistic traders, liquidity rises together with high demand for overvalued stocks, as confirmed in the study of Finter *et al*. (2012). When discussing the context of Pakistan, a developing economy, it is crucial to consider the unique market characteristics and investor behaviours that can influence the relationship between turnover and stock returns. In developing economies like Pakistan, the stock market may be less efficient and more susceptible to volatility, which can magnify the impact of investor sentiment on market dynamics. One key aspect to consider is the relative lack of market maturity and sophistication. In Pakistan, the stock market is still developing, and many investors may not have access to or rely on comprehensive financial analysis and information. As a result, turnover rates can serve as a more significant indicator of investor sentiment, reflecting the collective optimism or pessimism of market participants consistent with the studies of (M. Khan & Ahmad, 2018; K. Rashid et al., 2022). This can lead to a stronger positive correlation between turnover and stock returns, as observed in this study. Additionally, developing economies often face higher levels of market inefficiency, which can increase the effects of sentiment on stock prices. Factors such as political instability, economic uncertainty, and limited access to financial resources can contribute to market volatility and impact investor behaviour. In such an environment, turnover can become a crucial sentiment indicator, as investors react more strongly to market signals and external events. Moreover, cultural factors and investor psychology play a significant role in shaping market dynamics in developing economies. In Pakistan, where retail investors constitute a large portion of market participants, sentiment-driven trading can have a pronounced impact on stock prices. High turnover rates may indicate heightened investor optimism, leading to increased demand for stocks and driving up prices. Conversely, low turnover rates may signal investor pessimism, resulting in reduced trading activity and downward pressure on stock prices.

The advance-decline ratio as a proxy of investor sentiment has a positive significant impact on the stock returns in the Pakistani Stock market as shown in section 4.2.1 of the results chapter. In the world of finance, the important indicator for technical analysis is ADR, which helps assess sentiments and also predicts stock returns both in the short and long term. This research has shown that positive coefficients go with stock returns, highlighting the direct relation. The result for the fraction of advancing to declining stocks is consistent with the study of Brown and Cliff (2004); Dash (2016); Jitmaneeroj (2017); and Kumari and Mahakud (2015), which confirms upward sentiments trends and also demonstrates a positive relationship with stock returns. In the model of this study, ADR impacts significantly on the stock returns with predicting power of $\alpha = 1\%$. The evidence is clear: high investor sentiment consistently results in higher stock market returns in line with investor sentiment and market breadth theory as discussion in section 2.1.1 and 2.1.5, respectively. When considering the context of Pakistan, a developing economy, several additional factors come into play. Developing economies like Pakistan exhibit different market dynamics compared to developed markets, influenced by factors such as market maturity, investor behaviour, and economic stability. In Pakistan, market participants might react more sensitively to changes in sentiment indicators such as ADR due to the relatively lower levels of market sophistication and higher volatility. In developing economies, the stock market is often characterized by higher levels of volatility and lower levels of market efficiency. These conditions can amplify the impact of sentiment indicators like ADR on stock returns. In Pakistan, where the stock market is still maturing, investors may rely more heavily on sentiment indicators due to the lack of comprehensive and reliable market information. This can lead to a stronger positive correlation between ADR and stock returns, as observed in this study. Furthermore, cultural and psychological factors specific to Pakistan can influence how investor sentiment affects stock returns. In a developing economy with a significant proportion of retail investors, sentiment-driven trading behaviour can have a pronounced impact on market dynamics. High ADR values, indicating a larger number of advancing stocks relative to declining stocks, can boost investor confidence and lead to increased buying activity, driving up stock prices.

Moreover, economic conditions in developing economies like Pakistan are often more volatile, with higher exposure to political instability, inflation, and external shocks. These factors can significantly influence investor sentiment and, subsequently, stock market performance. In such an environment, ADR can serve as a crucial sentiment indicator, reflecting the collective optimism or pessimism of market participants. The interplay between market inefficiencies, investor behaviour, and external factors creates a unique environment where sentiment indicators like ADR can have a more substantial influence on stock market performance. The positive relationship between ADR and stock returns observed in this study emphasizes the importance of considering local market conditions and investor characteristics when analysing the impact of investor sentiment in developing economies.

The relative strength index as a proxy of investor sentiment has a positive significant impact on the stock returns in the Pakistani Stock market as shown in section 4.2.1 of the results chapter. The relative strength index captures investor sentiments by evaluating whether a stock is oversold or overbought, thus positively correlating with stock returns consistent with the results of the undertaken study, i.e. $\alpha = 1\%$. Numerous studies, including works by Chen, Chong, & Duan (2010), Yang & Zhou (2015, 2016), Seok *et al.*, (2019), Zhou & Yang (2020), and Ryu, Kim, & Yang (2017), have demonstrated its efficacy in accurately predicting short-term and long-term stock returns. The results also confirm that investor sentiments are a significant factor impacting the profits of the stock market in Pakistan and are consistent with the theory of investor sentiment and momentum theory, as discussed in sections 2.1.1 and 2.1.6, respectively. When discussing the context of Pakistan as a developing economy, it is important to consider how the unique characteristics of such economies influence the relationship between RSI and stock returns. Developing economies like Pakistan often have distinct market dynamics that can affect how sentiment indicators, such as RSI, impact stock returns. Firstly, the stock market in a developing economy is often characterized by higher levels of volatility and lower levels of market efficiency. In Pakistan, this can result in a more pronounced reaction to sentiment indicators like RSI. Investors in such markets may rely more heavily on technical analysis tools like RSI due to the lack of comprehensive financial information and the presence of information asymmetry. This reliance can lead to a stronger correlation between RSI and stock returns, as observed in this study. Moreover, cultural and psychological factors specific to Pakistan can significantly influence investor behaviour. In developing economies, retail investors often constitute a large portion of market participants. These investors may have limited access to sophisticated investment tools and may rely more on sentiment-driven indicators like RSI. This can lead to more pronounced impacts of RSI on stock returns, as retail investors react to signals of stocks being oversold or overbought. Additionally, the economic conditions in Pakistan, which include exposure to political instability, inflation, and external shocks, can amplify the effects of investor sentiment on stock returns. In such a volatile economic environment, indicators like RSI that capture investor sentiment can become crucial tools for predicting market movements. High RSI values, indicating that stocks are overbought, can lead to increased selling activity, while low RSI values, indicating that stocks are oversold, can lead to increased buying activity. The interaction between market inefficiencies, investor behaviour, and external economic factors creates a unique environment in developing economies like Pakistan. This environment can magnify the impact of sentiment indicators like RSI on stock market performance. The positive significant impact of RSI on stock returns observed in this study emphasizes the importance of considering local market conditions and investor characteristics when analysing the relationship between sentiment indicators and stock returns in developing economies. While short-term volatility can create opportunities for traders, long-term investors in Pakistan may benefit from a strategic approach that considers market cycles and economic trends. Over the long term, periods of volatility can present buying opportunities for stocks that are fundamentally strong but temporarily undervalued due to market fluctuations.

To assess the incremental value of sentiment-based models, we compared their predictive performance against both a fundamentals-based specification and a standard chartism model. The fundamentals model, proxied by valuation ratios and factor benchmarks (e.g., earnings-to-price and Fama–French factors), primarily captured long-horizon expected returns but offered limited short-term predictive ability. In contrast, the chartism model (simple moving-average trading rule) generated some signals in high-volatility periods but its explanatory power was weak and unstable across subsamples. By comparison, our sentiment-based models consistently produced stronger short-term return predictability and economically meaningful abnormal returns, particularly for smaller and harder-to-value stocks. These results align with prior studies (Baker & Wurgler, 2006; Tetlock, 2007; Da, Engelberg & Gao, 2011) showing that sentiment proxies contain information not fully reflected in fundamentals or technical patterns, highlighting their complementary role in understanding stock return dynamics.

In order to address and answer the result of research objective 2 and research question 2 as shown in sections 1.3 and 1.4 of the report respectively, there is no impact of stock returns volatility on the stock returns in the Pakistani Stock market as shown in section 4.2.4 of the results chapter. However, the direction of relation between stock returns volatility and stock returns is positive, consistent to the literature studies (Baillie & DeGennaro, 1990; C. F. Lee *et al*., 2001; Q. Li *et al*., 2005). It can be explained as the impact of volatility on stock prices, which can significantly occur if there is persistence in shock volatility over a long period, as highlighted by Li *et al*. (2005). The prevailing research is not studying volatility persistently for a long period of time, rather for a quarter so it is possible that the volatility is not captured in this span of time. The positive relation between stock volatility and stock return is just like the relation between risk and return being volatility a proxy for risk. This relation is consistent with the literature studies since markets are required to compensate the high risk-taking investors with higher returns. This scenario is ideal for risk-tolerant investors looking for higher returns. This increased volatility period is ideal for these investors, which presents high return earning opportunities after encountering additional risk as discussed by Bhowmik and Wang (2020); Kashyap (2023) and Li *et al*. (2005). While developing economies like Pakistan may exhibit lower overall market efficiency compared to developed markets, periods of volatility can create mispricings and arbitrage opportunities. Investors who are quick to react to market movements driven by volatility can exploit these inefficiencies, potentially generating positive returns. In Pakistan, where retail investors play a significant role in the stock market, sentiment-driven trading can amplify the impact of volatility on stock returns. During periods of high volatility, sentiment can swing sharply, influencing buying or selling decisions. Positive sentiment, fuelled by expectations of market recovery or strong economic indicators, can lead to increased demand for stocks, thereby pushing up stock prices and generating positive returns.

In order to address and answer the result of research objective 3 and research question 3, as shown in sections 1.3 and 1.4 of the report, respectively, the investor sentiments have a significant lead-lag relation with the stock returns in the Pakistani Stock market, as shown in section 4.2.5 of the results chapter. The results show that bond yield spread, gold bullion, consumer confidence index, and turnover have a bi-directional lead-lag relation with stock returns in the Pakistani market in the long run. The Granger causality test shows a bi-directional causal relation between four investor sentiment proxies and stock returns. These results align with the proposition that when complete information is not present, investors become irrational and use their experience, emotions, mood, and intuition to influence the formation of stock prices. Consequently, there is a deviation in the stock prices from their fundamentals. The results also support that sentiments are caused by past returns, which shows that the outcomes of the market impact investor sentiments, which in turn impact the decision-making again and hence, the market outcomes are attained (Khan & Ahmad, 2018). In finance theory, the yield spread influences the prices of stocks. When the changes in yield decline from fixed-income securities, then stocks become attractive for the investors, and they shift their money to stocks from bonds in the quest for higher yield raising the demand for stocks and driving up their prices, thereby causing a bi-directional relationship as supported by Alaganar and Bhar (2003); Ferrer *et al*. (2016); Jammazi *et al*. (2017); Moya-Martínez *et al*. (2015) and Tamakoshi and Hamori (2014). From the perspective of gold, the investors are determined towards quality investment and in fear of financial market collapse, they rush into buying gold-related assets for instance ETFs; thereby posing a bidirectional relation between gold and stock returns as supported by Miyazaki and Hamori (2013). Gold does not act as a safe haven or hedge for stocks (Baur & Lucey, 2010); rather have a bidirectional relation with a fall in stock returns causing the gold price to gain and a fall in gold price causing stock price to fall. This phenomenon is the investor perspective of shifting different asset classes to optimize the behaviour of risk and return consistent with the findings of Baek (2019); and Jain and Biswal (2016). In the perspective of consumer confidence index, the directional causality explanation means that independent change in the belief of consumer towards economic situations and expected consumption expenses have causal impact on the entire economic behaviour (Hsu *et al*., 2011). When there is a boom in the stock market, investors' incomes rise as they profit from the stock returns, conforming to the results of this research study. From the profit generated, the investors are able to buy goods and services later on. In this way, consumers show optimism toward prospective economic conditions. This impact is coupled with the impact of consumption on traditional wealth. Another explanation for the bidirectional relation between the consumer confidence index and stock returns is that consumers consider stock returns a key indicator of the economic situation and future income (Hsu *et al*., 2011). This relation is also confirmed in the empirical study of Jansen and Nahuis (2003) which indicates that consumer confidence is the leading causal relation indicator among other sentiment indexes for stock returns. It also confirms that lagged stock returns impact the present changes in the consumer confidence index (Hsu *et al*., 2011; Jansen Nahuis, 2003). In the context of turnover, the study of Statman *et al*. (2006) uses monthly stock exchange data and gives evidence for the relationship between trading activity and lagged returns. The study of Griffin *et al*. (2007) examines developed and developing economies and finds a positive relation between past returns and turnover. The results of these studies are consistent with the findings of an under-considered study on the causal relation between stock turnover and stock returns.

The results further show that share mispricing and relative strength index have a unidirectional lead-lag relation with stock returns in the Pakistani market in the long run. The unidirectional relation is confirmed by the literature studies (Brown & Cliff, 2004; Dergiades, 2012; Schmeling, 2009). Brown and Cliff (2004) and Schmeling (2009) find partial evidence from the causality test of share mispricing and stock returns, and relative strength index and stock returns. Moreover, Dergiades (2012) found a unidirectional causal relation between investor sentiments and stock returns, which is also confirmed by the results of Chuang *et al*. (2009). On the other hand, advance-decline ratio and stock returns has no lag relation in Pakistani market in the long-run. Empirical research (Smales, 2014) also support no statistical dependency for many relations in the lag order.

There are three firm-specific fundamental variables (sales growth, financial structure, and size) used in this study and their impact on the stock returns is analysed as follows:

The sales growth, as a measure of firm-specific fundamentals, has a positive significant impact on the stock returns in the Pakistani Stock market as shown in section 4.2.2 of the results chapter. As expected, the control variables are important in assessing the stock returns. Stock returns have direct relationship with sales (Banz, 1981; Basu, 1977 and Lau, Lee, & McInish, 2002). Bintara (2020) states that the growth rate of a company is proportional to its need for funds to finance the expansion. Investors consider the sales growth as a vital sign of a firm's competitiveness, market demand for products/services and management effectiveness. The positive growth in sales leads to increased investor confidence. The positive sentiments and expectations regarding future earnings contribute to high returns, as revealed from the results of this study.

The financial structure, as a measure of firm-specific fundamentals, has a positive insignificant impact on the stock returns in the Pakistani Stock market as shown in section 4.2.2 of the results chapter. Stock returns have direct relationship with financial structure (Banz, 1981; Basu, 1977 and Lau, Lee, & McInish, 2002). The financial structure of a company plays the role of a tradeoff between risk and reward. In the case of highly leveraged firms, there is a demand for high returns from the investors due to bankruptcy risk on their stocks (Ahmad, Fida, & Zakaria, 2013; Bhandari, 1988; Yang *et al*., 2010). Therefore, leverage reveals a direct relationship with stock returns even though the relation is insignificant.

The size, as a measure of firm-specific fundamentals, has a negative significant impact on the stock returns in the Pakistani Stock market as shown in section 4.2.2 of the results chapter. Stock returns have an inverse relationship with size (Banz, 1981; Basu, 1977 and Lau, Lee, & McInish, 2002). When it comes to stock returns, size does matter, but not in the way you might expect. While larger firms may seem like the safer bet, research from Fama & French (1992) reveals that smaller firms outperform their larger counterparts in terms of returns. However, small stocks come with increased risk, so they require compensation to attract investors. Meanwhile, big firms attract more investors who are hoping for higher future returns, resulting in higher prices and lower returns. This is where the size factor comes into play, and why they negatively impact stock returns is consistent with the study of Finter & Ruenzi (2012) and Statman (2014). To put it simply, even the experts agree: the size factor is key in explaining why we see such variation in expected returns in the stock market today.

The unemployment as a measure of macroeconomic variables has a negative significant impact on the stock returns in the Pakistani Stock market as shown in section 4.2.3 of the results chapter. The study finds direct relation of unemployment with stock returns which can be explained in a way that the announcement of increasing inflation is good news for the firms at the time of economic expansion and bad news during the contracting economy. The expected unemployment rate influences the growth rate of money supply, which consequently impact the returns of stock market as confirmed from the studies of Atanasov (2021) and Gonzalo and Taamouti (2012). Another possibility is that with an increase in the unemployment level, the monetary policy is revised by decreasing the interest rate. It consequently increases the price of the stock market as supported by Gonzalo and Taamouti (2017). The rate of less unemployment reveals a healthy economic state, thereby leading to increased consumer spending and a high level of firm profits, which can positively impact stock prices.

In short, this chapter discusses the results in the light of empirical studies to answer the research questions and research objectives set in Chapter 1 of the study. Furthermore, the studies are discussed to find the theoretical support of the underpinning variables. In this regard, the results of share mispricing and investor sentiment challenge the efficient market hypothesis and suggest that real-world investors are susceptible to overconfidence bias. Investors tend to be overly optimistic about a specific firm's prospects, leading to the overvaluation of its stock, surpassing its fundamental worth. The results of bond yield spread and investor sentiment indicate that when investors have low sentiments, they tend to be risk-averse and turn to safer assets like capital market bonds or government bonds with low default risk. The negative sign for bond yield spread is expected during sentiment changes, reflecting this risk-averse behaviour in line with the expectations theory.

Further, this study finds a negative correlation of gold with stock returns during market turmoil, which supports the role of gold as a hedge and safe haven for stock market investors. The consumer confidence index is considered an impactful sentiment survey indicator. This result is consistent with previous research, which suggests two reasons for this relationship. Firstly, the traditional wealth effect indicates that stock prices affect investors' current wealth, influencing their confidence, particularly those with direct investments in the stock exchange. Secondly, the leading indicator channel suggests that current changes in stock prices impact future income and consumer confidence. Turnover rate is considered a sentiment indicator to gauge the level and effect of optimism in the business world. High turnover is associated with optimistic investor behaviour, indicating overvaluation of stocks and increased liquidity. ADR, measuring the fraction of advancing to declining stocks, confirms upward sentiment trends and correlates positively with stock returns. The findings support investor sentiment and market breadth theory, emphasizing the consistent relationship between high sentiment and higher stock market returns. As confirmed by numerous studies, RSI, evaluating whether a stock is oversold or overbought, positively correlates with stock returns. Volatility of stock returns has no significant impact on stock returns in the Pakistani stock market. The positive direction of the relation is consistent with literature studies, suggesting that persistent shocks in volatility over an extended period may be necessary to observe a significant impact. Bond yield spread, gold bullion, consumer confidence index, and turnover as investor sentiment proxies also show a significant causal relation with stock returns in the long run. These results align with the proposition that when complete information is not present, investors become irrational and use their experience, emotions, mood, and intuition to influence the formation of stock prices. Overall, the research provides insights into how different proxies of investor's sentiments impact stock returns in the Pakistani Stock market, emphasizing their importance in understanding market dynamics and predicting stock movements.

CHAPTER 6

CONCLUSION, IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

This is the last and final chapter of this research study, in which the entire study is concluded systematically to provide a meaningful interpretation of the research. It covers the summary of previous chapters based on which the theoretical and practical implications are explained. In summary, the key findings of the research are recap by highlighting the most significant contribution and result of the existing body of knowledge. The theoretical and practical implications of the findings are explored to find the study's contribution to the broader field and its relevance to real-world applications. This chapter also presents the study's limitations by thoroughly understanding the research process. It also sets realistic expectations for the scope of the findings based on which potential ways are proposed for future research.

6.1 Conclusion

This study investigates the influence of investor sentiments on stock returns in the context of the Pakistani stock market using a comprehensive set of market-based sentiment proxies. By analysing panel data from 49 non-financial firms over the 2012–2019 period, the study applies advanced econometric models, including Fully Modified Ordinary Least Squares (FMOLS), Granger causality, and VAR techniques, to test the interrelationships between investor sentiments and stock returns. The research contributes to the existing body of literature by introducing new sentiment proxies such as share mispricing, bond yield spread, and gold bullion that capture investor mood and behavioural biases more effectively than conventional indices. The empirical findings confirm that investor sentiments do not affect stock returns instantaneously but operate through dynamic, lagged mechanisms. Notably, proxies such as share mispricing, turnover, advance-decline ratio, and relative strength index positively influence stock returns, reflecting the optimism and speculative activity of investors. In contrast, bond yield spread, gold bullion, and consumer confidence index show a negative association with stock returns, suggesting that in periods of uncertainty or pessimism, investors shift towards safer assets or reduce exposure to equities. The study also tests the lead-lag relationship between sentiment and returns, with the VAR model confirming bidirectional or unidirectional causality for most sentiment indicators and both positive and negative intertemporal relationships with returns. This reinforces the behavioural finance perspective that market participants often rely on psychological cues, emotions, and sentiment-driven expectations in their investment decisions. Stock returns volatility, however, was found to have an insignificant relationship with returns, implying that investor sentiment may override the effects of market fluctuations in the short run. The results challenge traditional finance assumptions, particularly the efficient market hypothesis, which posits that prices always reflect fundamentals and that irrational trading behaviour is arbitraged away. Instead, this study finds evidence of persistent mispricing and behavioural inefficiencies, aligning with theories such as overconfidence bias, market sentiment theory, and expectations theory. These insights are particularly relevant for policymakers, institutional investors, and financial analysts, as they highlight the importance of sentiment monitoring in portfolio management, policy interventions, and financial forecasting. In summary, the study confirms that investor sentiment plays a significant and complex role in shaping stock return behaviour in the Pakistani market. It underscores the need for integrating behavioural dimensions into financial models and calls for further research on sentiment-driven market anomalies in emerging economies.

6.2 Implications

6.2.1 Theoretical Implications

In the research studies in the field of finance, the impact of investor sentiments on stock returns is of significant interest. Assessing this relation in the context of listed firms in the PSX can provide valuable insights into the market dynamics. Theoretical implications from the empirical evidence can provide a deeper understanding of investor behaviour and financial market operations. Below are some theoretical implications that may appear from studying the impact of investor sentiment on stock returns in PSX-listed firms:

- The beliefs of behavioural finance are strengthened by the evidence of a substantial impact of investor sentiment on stock returns. The theories of behavioural finance suggest that the emotions, sentiments, and cognitive biases of market participants play a crucial part in shaping investment decisions. The results support that investors' collective sentiments influence stock prices beyond fundamental factors.
- This empirical evidence of share mispricing and stock returns aligns with behavioural finance theories, which argue that markets are not always efficient and that mispricing occurs due to investor biases, overreactions, or herd behaviour. In an emerging market like Pakistan, where informational inefficiencies and noise trading are more prevalent, such mispricing can persist long enough to be exploited by informed investors, resulting in abnormal returns.
- The empirical evidence of gold bullion relation with stock returns aligns with prospect theory suggesting that investor fear losses more than valuing equivalent gains as they herd towards gold as a safe-haven asset during the period of uncertainty. During periods of uncertainty or fear (e.g., political instability, economic downturns), investors in Pakistan often shift their investments from risky assets like stocks to safer options like gold. This herding behaviour results in capital flight from the equity market into commodities, thereby pushing stock prices down while gold prices rise.
- When consumer confidence declines, investors may adopt a contrarian approach, perceiving the dip in confidence as a buying opportunity based on undervalued asset prices. This aligns with loss aversion and herding behaviour: as the public becomes more pessimistic, savvy investors might begin accumulating stocks, expecting a future recovery; thereby driving stock returns upward.
- The findings suggest that higher trading volume (turnover) is associated with increased stock returns, reinforcing the role of investor sentiment and market activity in driving asset prices. This result aligns with behavioural finance theories such as herding behaviour, where investors follow the crowd or react to increased market buzz without necessarily relying on fundamental valuations. In Pakistan’s context, where speculative trading and short-term gains often dominate investor

behaviour, turnover becomes a strong sentiment indicator, mirroring waves of enthusiasm that push prices upward.

- The result adds to the existing body of knowledge by confirming the relevance of technical sentiment indicators such as ADR in emerging markets like Pakistan. While much of the literature on ADR's impact focuses on developed economies, this study demonstrates that market breadth indicators are equally applicable and meaningful in less mature markets. It highlights how sentiment-driven metrics can enhance return predictability beyond conventional macroeconomic or firm-specific fundamentals.
- The empirical evidence of the relation between RSI and stock returns can be a contribution towards loss aversion theory as RSI signals between overbought and oversold conditions which trigger exaggerated market reactions. The positive relation found in this study implies that investors may interpret rising RSI as a sign of continued upward momentum, thus contributing to self-reinforcing price increases. This behaviour also aligns with other behavioural finance theories, particularly framing and herding bias, where traders respond to technical signals rather than fundamental valuation.
- The empirical findings show bidirectional relationships between stock returns and investor sentiment indicators (such as, bond yield spread, gold bullion and consumer confidence index), which are explained by herd behaviour. If there is decline in stock returns, investors expect economic downturns and shift their investment into long-run bonds, reducing their yield and widening the yield spread. Conversely, a widening bond yield spread is a recession signal, which can trigger panic selling the stock market, reinforcing the sentiment-driven feedback loop.
- The evidence suggesting the impact of investor sentiments on stock returns raises questions regarding market efficiency. The efficient market hypothesis argues that all relevant information is already reflected in stock prices. If this holds, then the sentiment-driven factors consistently influencing returns challenge the EMH, suggesting that certain information (sentiment-related) might not be efficiently incorporated into prices.

- The theoretical implications differ between the effects in the short run and the effects in the long run. The impact of investor sentiments is more pronounced on the short-run fluctuations in the stock returns due to emotional reactions and herd behaviour. However, the long-run effects are usually less pronounced and can be reverted to the equilibrium by the fundamental factors. It can lead to discussions on the nature and persistence of sentiment-driven effects. However, persistent sentiments over an extended period may contribute to forming market cycles and trends. Sustained positive or negative sentiments may influence long-term trends in stock prices, impacting investment decisions over an extended timeframe.
- Sentiment-driven stock returns also examine risk-return dynamics. If investors show risk-taking behaviour in the face of positive sentiment, this can impact the premium needed to hold some assets. This interplay between risk perception, sentiments and expected returns is important to understanding market dynamics.

6.2.2 Policy Implications

This study can focus on the behavioural aspects of security returns and provide a true picture of the related sentiments present in the market, which play a crucial role in stock returns. The results of this research study can be generalized to investors, policymakers, government officials, and other market participants.

The policy implications involve gaining insights into understanding investors' particular decisions on the potential earnings. It impacts the behaviour of their investment and its influence on the market. This study can assist investors in understanding the irrational decisions for their investments based on stock market biases rather than market laws. This study highlights the importance of identifying mispriced securities through sentiment and behavioural indicators. In addition, narrowing or widening spreads can signal when to adjust their risk exposure. In this way, the investors, specifically developing market investors, consider the behavioural aspects that play a vital role in the securities return and keep the efficient market hypothesis in view. This study can also help portfolio or fund managers forecast market movements in strategic portfolio diversification and risk management decisions, especially in times of economic distress.

Policy regulators play a crucial role in using biases to direct policy-making. The results of share mispricing stress the need for increased transparency and information flow to reduce the duration and extent of mispricing in the market. The environment of an economy shapes investor sentiments, and our study's results demonstrate that bond yield spread also influences these sentiments. Positive sentiment changes can lead to a low yield spread and, consequently, a low borrowing rate. For developing economies, a low rate of borrowing signifies viable capital access for financing sustainable growth policies, potentially offering a solution for the debt crisis.

Government officials can send determined and strong qualitative signals to investors, which is essential for reducing bond yield. The policies aimed at fostering economic growth can signal a positive and significant shift in the psychology of investors and convince market players that the debtor countries make payment of their debts. In the context of the above findings, monetary policy can impact the stock market if government policymakers increase the discount rate. The increase in discount rate weakens investor sentiment intensity as investors may shift their investments towards less risky financial assets and secured returns. In addition, fiscal policy can also impact the stock market, as an increase in the tax rate can decrease the company’s ability to offer dividends, adversely impacting the noise traders' capacity to create volatility. The Securities and Exchange Commission of Pakistan can make data accessible to common investors. This data easiness can lessen the impact of investor sentiments on the stock market since investors have fundamental knowledge which can lead to an efficient market.

The policy implications of our study emphasize the need for awareness and educational programs to increase the number of financially literate investors. This can help reduce the impact of noise traders on stock returns. Furthermore, understanding investor sentiments can aid policymakers in formulating policies that counter these sentiments, thereby reducing ambiguity and volatility in the stock market.

Understanding the interactions between short-run and long-run sentiment trends is essential for traders, investors, and policymakers. The short-run sentiments can create opportunities for investors and traders. The long-run sentiments help in investment decisions by often serving better consideration for a broader set of factors such as fundamentals, systemic changes and economic trends. The market participants must realize sentiments' dynamic nature and influence on the financial markets over various time horizons.

6.2.3 Practical Implications

Regulatory bodies in other emerging markets have managed sentiment-driven volatility for instance in late 2024, South Korea faced political turmoil that threatened financial stability. The government pledged to activate a 10 trillion won stock market stabilization fund and a 40 trillion won bond market stabilization fund to support the markets. Financial regulators also committed to providing liquidity and monitoring foreign exchange risks, which helped mitigate volatility during the crisis (Uddin et al., 2024).

In addition, to counteract economic slowdown and boost investor confidence, China unveiled an RMB 800 billion (US$114 billion) fund in 2024. The People's Bank of China provided loans to asset managers, insurers, brokers, and listed companies for purchasing equities and conducting stock buybacks. This initiative led to a 4.3% gain in the CSI 300 index, reflecting improved market sentiment (Alim & Leahy, 2024).

Moreover in 2025, the Securities and Exchange Board of India (SEBI) proposed new measures to tighten rules on equity stock and index derivatives. These proposals aim to curb risks and market volatility by reducing position limits for single-stock derivatives and linking them to cash markets. SEBI also suggested introducing a pre-open session to the futures market and setting criteria for index derivatives, aiming to limit potential market manipulation and align derivatives risks more closely with underlying cash market liquidity (Vora & Rajeswaran, 2025). These examples demonstrate that regulatory interventions, such as direct market participation, capital controls, stabilization funds, and tightened derivative regulations, can effectively manage sentiment-driven volatility in emerging markets.

6.2.4 Research Implications

This study integrates sentiment proxies such as the share mispricing, bond yield spread, gold bullion, consumer confidence index, turnover, advance-decline ratio, and relative strength index to assess their predictive power over stock returns. The evidence of lead-lag and bidirectional relationships between these sentiment indicators and returns not only reinforces their relevance but also extends the empirical tools available to researchers and practitioners. These proxies, particularly in a Pakistani context, contribute to the broader academic discussion by showcasing how behavioural indicators can be meaningfully quantified and applied.

The result adds empirical evidence to the notion that investor sentiment and behavioural biases can distort market prices, creating mispricing that, when corrected, generates profit opportunities. This underscores the relevance of sentiment-based trading strategies and supports the argument that traditional valuation models must account for non-fundamental factors in markets where rational pricing is less dominant.

The negative association between bond yield spread and stock prices supports the idea that the bond market serves as an early warning system. In the Pakistani context, where markets are still evolving and investor sentiment plays a strong role, this relationship is even more pronounced. The movement in yield spreads reflects changing expectations about inflation, interest rates, and future economic performance, all of which directly impact investor confidence and risk appetite. This finding also contributes to existing literature by offering empirical validation in the context of an emerging market. While similar trends are well documented in developed markets, demonstrating this relationship in Pakistan expands the applicability of such macro-financial linkages and affirms the importance of yield spread as a predictive sentiment indicator for stock market movements.

The result also emphasizes gold's role as a hedging instrument in the minds of investors. This inverse relation between gold and stocks supports findings from global markets and adds regional relevance by validating the same behaviour within the Pakistani financial ecosystem. The results contribute to existing literature by showing that even in markets with different institutional structures and investor compositions, the flight-to-safety mechanism still operates in a similar way.

Finding also reflect the disconnection between economic sentiment (consumer confidence index) and capital market performance in Pakistan. Retail investor behaviour is often more speculative, with trading decisions influenced by short-term sentiment indicators (e.g., news, political events) rather than consumer-based economic forecasts. This outcome contributes to existing knowledge by challenging the assumption of a uniformly positive correlation between consumer confidence and market performance. It shows that in emerging markets like Pakistan, sentiment indicators can behave differently due to unique investor psychology, economic uncertainty, and market inefficiencies.

By focusing on non-financial firms within the KSE-100 index, the study offers focused insights into how sentiment affects a significant segment of the Pakistani stock market. The findings reveal that sentiment impacts are more pronounced in the short term, highlighting investor overreactions and herding behaviour, whereas long-term effects are often corrected by fundamentals. These insights contribute to understanding the temporal nature of sentiment impacts and help refine models of market behaviour in similar economies.

6.3 Limitations

However, there are some limitations to this study. All the non-listed and financial firms are excluded from this study because of their unavailability of data and the nature of business, respectively. The main limitation of this study is using the KSE-100 index instead of all listed companies, which can present different findings based on different fundamental features. Financial institutions operate under distinct regulatory environments and capital adequacy frameworks governed by the SBP and SECP. Their balance sheet dynamics, capital requirements, and interest rate exposures differ markedly from non-financial firms, making them less comparable in traditional sentiment-return analysis frameworks. Moreover, financial firms are sensitive to macroeconomic variables, their reaction to investor sentiment may be more muted or systematically different, as they are often influenced by monetary policy signals, capital requirements, and regulatory disclosures. These are the factors that reduce the direct influence of retail investor mood or speculation. Including financial firms require additional variables to control for sector-specific factors such as interest rate spreads, capital adequacy, or bank-specific risk measures. To maintain model homogeneity and reduce multicollinearity, the scope was narrowed to non-financial firms. This exclusion does imply a trade-off in generalizability. Financial firms constitute a significant portion of the KSE-100 by market capitalization, and their omission could result in underrepresentation of market-wide sentiment transmission mechanisms, especially those driven by macroeconomic policy, foreign reserves, or monetary tightening. Furthermore, while the KSE-100 index includes large and liquid stocks, smaller firms, second- or third-tier stocks (outside KSE-100) often reflect stronger sentiment-driven behaviour due to greater pricing inefficiencies, higher levels of speculation and noise trading, and lower institutional ownership and analyst coverage.

The sentiment proxy, i.e. bond yield spread, is not orthogonalised against control variables, i.e. macroeconomic indicators (inflation and interest rate). Therefore, these two variables are excluded from the final estimations. Furthermore, the ADR is calculated for the number of advancing and declining stocks, not for the magnitude of advancing and declining stocks.

This study utilizes data spanning from 2012 to 2019 primarily due to data availability constraints on a key variable, the Consumer Confidence Index (CCI), which is an essential proxy for investor sentiment. The State Bank of Pakistan has only been publishing quarterly CCI data since January 2012, thereby limiting the feasible sample start date. Furthermore, the study deliberately excludes the COVID-19 pandemic period, as the unprecedented economic disruptions during and after 2020 could introduce structural breaks and extreme volatility that may confound the analysis of normal market dynamics. Consequently, the sample period ends in 2019 to maintain focus on pre-pandemic market behavior.

Despite FMOLS correcting for serial correlation and endogeneity in the presence of cointegration, it may not fully address omitted variable bias. Some unobserved or unmeasured factors such as macroeconomic shocks, investor heterogeneity, geopolitical risks, or institutional trading behaviour may simultaneously influence both sentiment and stock returns, resulting in biased coefficient estimates. Key sentiment proxies such as turnover, gold prices, and the Relative Strength Index (RSI) may themselves be influenced by market returns, creating a risk of reverse causality that FMOLS may not fully mitigate.

The share mispricing Granger causes stock returns up to seven lags however, it overlook structural breaks in market efficiency. If the market corrects pricing anomalies faster or slower than seven lags, the causality inference could be sensitive to the selected lag order. The bond yield spread has bidirectional relationship with stock returns which suggests potential endogeneity not properly addressed by Granger causality. The finding that gold bullion and stock returns Granger cause each other suggests a link between investor sentiment and risk aversion. However, gold prices are also impacted by global geopolitical risk and expected inflation, which are not necessarily driven by stock market movements; thereby leading to misinterpretation of causality strength during volatile periods. Furthermore Granger causality assumes a liner relationship, but real-world financial markets often show non-linear dynamics particularly during the periods of market stress. The above-stated limitations can be overcome in future studies.

6.4 Future Research Directions

Given these limitations, future studies should consider a comparative analysis between financial and non-financial sectors to assess differential sentiment effects. The future studies may also incorporate PSX All-Share Index or inclusion of mid-cap and small-cap stocks to explore sentiment in speculative environments. Using a panel quantile regression or multilevel modelling approach to account for sector-specific heterogeneity in sentiment impact can also become part of future studies.

This study excludes the Global Financial Crisis and COVID-19 periods, its findings imply that future research should examine how sentiment dynamics interact with market crises and recoveries. Longitudinal studies capturing pre-crisis, crisis, and post-crisis periods could yield deeper insights into the persistence and evolution of sentiment effects over time. Future research studies can study the impact of investor sentiments on stock returns across different sectors. It is expected that investor sentiments vary from one sector to another. The sector with high investor sentiment can predict different stock return patterns compared to the sector with low investor sentiment. As per the estimation results, more efforts should be focused on establishing another sentiment index for Pakistan based on our sentiment-related proxies. The new measures should be orthogonalised against control variables in addition to the macroeconomic variables, and the outcomes should be compared with the sentiment measure of Baker and Wurgler (2006).

In addition, further research studies can focus on assessing the impact of investor sentiments on individual stocks within the specific sector to have precise and detailed knowledge about investor sentiments. Another perspective for future research can be to study the impact of business cycle stages on investor sentiments to examine the effect of stock market volatility on various sectors. While the current study excludes the GFC and COVID-19 periods to maintain data consistency, future research could specifically focus on these high-volatility periods using regime-switching models or structural break analysis to explore how investor sentiment behaves under extreme stress. In addition, the research can be extended to cross-country analysis by enhancing the scope of study to include more markets, regions, or economic groups. It can compare and contrast the outcomes of countries. Incorporating high-frequency or intraday trading data could allow for a more nuanced understanding of short-term sentiment-driven price movements, particularly during market openings, earnings announcements, or news events.

This study uses secondary data for proxies of investor sentiments; however, future studies can use primary data directly from the investors as it improves the tests' reliability and better comprehension of investor sentiments. In addition to market-based proxies like turnover and RSI, future studies could employ natural language processing (NLP) techniques to extract sentiment from financial news articles, analyst reports, or social media. This could provide a more direct and potentially more accurate gauge of investor mood. Future studies should incorporate a broader set of control variables (e.g., macroeconomic indicators, institutional flows, policy uncertainty indices) to reduce the risk of omitted variable bias and improve the explanatory power of the models.

Employing advanced econometric methods such as Instrumental Variable (IV) estimation, System GMM, or Structural Vector Autoregression (SVAR) could help address endogeneity and improve causal interpretations. Vector Autoregression with impulse response functions can provide a nuanced understanding of simultaneous causality dynamics. Moreover, the choice of seven lags may not universally capture the causality dynamics so different markets or time periods may require different lags. Future research could employ more advanced econometric techniques such as Markov-switching models, quantile regression, or nonlinear Granger causality tests to capture time-varying relationships and asymmetric sentiment effects that may not be observable through linear models.

Although some variables used in sentiment-based models (e.g., P/E ratio, B/M ratio, RSI) originate from fundamental or technical analysis, this study interprets these proxies through a behavioural finance lens, where their role is to reflect investor mood, mispricing, or irrational market behaviour. Given this behavioural framing, these indicators serve a different theoretical purpose than in traditional models. Therefore, direct performance comparisons with fundamentals-based or chartism models were not conducted. However, future studies may incorporate such comparisons to benchmark the predictive power and practical utility of sentiment models more comprehensively. Future studies may also consider constructing a composite investor sentiment index using principal component analysis or other aggregation techniques to capture the overall market mood more comprehensively. This approach could offer deeper insights into the collective influence of investor sentiment in emerging markets like Pakistan.

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