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Investor Sentiment Dynamics and Returns in Emerging Equity Markets

by

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This dissertation is proudly dedicated to my dear father Rafaqat Ali, praiseworthy mother, my uncle Zahoor Ahmed Gondal, my research supervisor Dr. Arshad Hassan and Mr. Khalid Mehmood

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Abstract

The present study is aimed to examine the effect of different levels of investor sentiment on current and future equity returns at different time horizons in the presence of market volatility and selected macro factors. Secondary data is collected from representative indices BOVESPA, RTSI, JCI, NSEI Nifty 50, SHCOMP, JSE, PSX of Brazil, Russia, Indonesia, India, China, South Africa, and Pakistan (BRIICSP) respectively from 'Investing.com,' 'yahoo finance,' 'world data bank,' OECD, websites of central banks of selected countries for a period from 2001 to 2020. Daily share prices are converted into returns, and data on macroeconomic variables are converted from monthly to daily. Principal Component Analysis is applied to construct Investor Sentiment Index by taking Trading Volume and Turnover Ratio as proxies. The impact of investor sentiment on returns in different contexts is calculated for each country separately and then grouped for a panel study. Auto-Regressive Model/Auto Regressive Moving Average Model are applied for country-level analysis, and Dynamic Panel Model/ Dynamic Fixed Effect Model is applied for group-level analysis.

Investor sentiment significantly impacts current market returns, and this influence is continued in the short run in most of the sample countries. However, the impact of sentiment is less prominent in the longer run. Optimistic and pessimistic states of investor sentiment significantly affect equity returns and volatility in all countries in both linear and non-linear terms. At a moderate level, investor sentiment shows a significant effect on returns, an extremely optimistic level shows a significant effect in all the countries except Brazil and South Africa, and an extremely pessimistic level shows a significant effect for all the countries except Brazil. Pessimistic investor sentiment has a negative effect on the relationship of VaR-95 and VaR-99 with equity returns in all the countries individually and also at the panel level, whereas optimistic investor sentiment has a negative effect in Russia, Indonesia, China, and Pakistan and a positive in Brazil, India, and South Africa at country level as well as at group level. Pessimistic investor sentiment has a significant negative effect on the relationship between CVaR-95 and equity returns in all the selected countries at the individual level as well as at the aggregate level,

whereas optimistic investor sentiment has a significant positive effect in Brazil and South Africa and negative effect in Indonesia, China, and Pakistan. During the epidemic, the pessimistic investor had a significant effect on returns in all of the selected countries and at the group level except Brazil, whereas optimistic investor sentiment had a significant effect on equity returns in Indonesia and South Africa only. Changes in risk-free rate and term spread also show a significant effect. It is concluded that different levels of investor sentiment significantly impact the market returns concurrently and in the short term, even in the presence of different macroeconomic and risk factors.

Therefore, decision-makers should emphasize sentiments, at least in the short run. The study's findings may help investors better understand the market trends under the influence of sentiments, and portfolio managers and risk professionals can devise their strategies accordingly. The study may be extended with more proxies, markets, and time limits to reach a generalized result.

Contents

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Abbreviations

ABM	Agent-Based Model
ANN	Artificial Neural Network
AR	Auto-Regressive
ARDL	Autoregressive Distributed Lag
BRIICSP	Brazil, Russia, Indonesia, India, China, South Africa, Pakistan
CCI	consumer confidence index
DNN	Deep Neural Network
EBSD	Economics Blogs Sentiment Divergence
EBSI	Extreme Bright Sentiment Indicator
EDSI	Extreme Dark Sentiment Indicator
GEM	Growth Enterprise Market
GSVI	Google Search Volume Index
IPI	Industrial Production Index
IPO	Initial Public Offerings
IPO	Initial Public Offerings
IRF	Impulse Response Functions
ISI	Investor Sentiment Index
IS-P	Purged Sentiment Index
KLCI	Kuala Lumpur Composite Index
MP	Market Premium
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Square
PCA	Principle Component Analysis
POE	Privately Owned Enterprises
PRE	Prediction Rule Ensembles

QR	Quantile Regression
RP	Risk Premium
SBW	Sentiment Index of Baker and Wurgler
SENTIM	Sentiment
SET	Stock Exchange of Thailand
SOE	State-Owned Enterprises
STR	Smooth Transition Model
TB	T-Bills
TS	Term Spread
VaR	Value at Risk
VAR	Vector Autoregressive
VIX	Investor Volatility Index

Chapter 1

Introduction

The Efficient Market Hypothesis of Fama (1970) provides the foundation for the concept of efficient markets that has been one of the most important paradigms of traditional finance theories proposed by great scholars (Markovitz, 1959; Miller, 1961; Sharpe, 1964; Linter, 1965; Black, 1972; Black and Scholes, 1974). Traditional theories are based on the assumptions that (a) investors are always rational, (b) information is equally disseminated to all investors, (c) investors make decisions in the same manner, (d) prices remain fair in the markets, and (e) investors are unable to gain abnormal profits. The proponents of these theories claim that these theories provide a simple and plausible explanation of the market phenomena and are applicable in different market conditions.

Due to these reasons, these theories have remained the research focus over the years. For a better understanding of asset prices and returns, traditional asset pricing models, such as the Capital Asset Pricing Model (Sharpe, 1964), Arbitrage Pricing Theory (Ross, 1976), and the Fama and French (1996, 2015) have been used for the several decades. These models have contributed to developing and refining the Efficient Market Hypothesis. The crust of traditional finance theories is that investors drive the stock market toward fair prices. However, it is a common observation that bubbles and speculations exist in the financial markets; one of the reasons is that investors are not always logical, and their decisions are influenced by emotions, cognitive biases, and personal thinking styles. This results in significant deviations in stock prices compared to their intrinsic values. These phenomena remain unexplained by traditional finance theories.

In order to explain these abnormal observations in the financial markets, scholars try to obtain support from human psychology. Resultantly, a new financial paradigm, called behavioral finance, emerges in the financial markets that assumes a) investors are not always rational, (b) information is not equally available to all investors, (c) investors do not make rational decisions, (d) prices fluctuate in the markets, and (e) investors are able to gain abnormal profits at least in the short run. These market realities provide foundations for behavioral finance, which has been an important field of study for practitioners and academicians, and it helps to understand the asset pricing process in financial markets.

Behavioral asset pricing theory is empirically tested by using various asset pricing models, but according to Shefrin (2009), there is no consistency, uniformity, or coherence in models to explain the phenomena. Despite serious criticism, behavioral finance theory is recognized as a descriptor of investors' behavior regarding the stock market. It provides a cogent explanation of the abnormal behavior of market prices observed in the financial equity markets. According to Zhang and Yang (2009), the unexpected fluctuations in market pricing are either due to the proper use of incorrect information or the investors' inaccurate use of correct information. These two possibilities are considered responsible for the initiation of specious beliefs in the minds of irrational investors.

Tversky and Kahneman (1992) discuss various forms of investor irrationality and conclude that investors' cognitive and emotional biases play a vibrant role in determining the behavior of the investors, which results in biased investment decisions. This type of cognitive and emotional disparity is more commonly observed in investors under the control of their instinct, and their behavior is directed by their sentiments (Keynes, 1936). This investor's psychological disparity about the financial markets is termed "investor sentiment" and is an important component of behavioral finance. The animal spirit theory of Keynes (1936) and the prospect theory of Tversky and Kahneman (1992) explain the way sentiment drives demand and supply. Investor sentiment is derived from a sustained idea, a thought, an opinion, and feelings about a specific phenomenon and consequently influences market behavior. The idea of Keynes (1936) that investor sentiment might influence stock prices is supported by many studies (Baker and Wurgler, 2006; Gao and Xie, 2020; Zou and Sun, 2012).

Investor sentiment means the mindset of investors in a particular stock market. Investors decide their entry and exit in the market, considering the market sentiment indicators, and adopt suitable trading strategies to optimize their returns. Sentiments are categorized as optimistic and pessimistic (Baker and Wurgler, 2006) and are responsible for the deviation of asset prices from their base values (Ling et al., 2010). This deviation of prices is attributed to uninformed demand shocks and arbitrage limitations. Uninformed traders are responsible for sentiment-based demand shocks, whereas arbitrage limitation prevents informed traders from correcting this mispricing, and thus deviations remain persistent in the market (Baker and Wurgler, 2006). Optimistic investors believe themselves good in positive situations, expect high market prices, and indulge in extraordinary buying to get high payouts; this results in overvalued prices in the market. Whereas pessimistic investors consider themselves more vulnerable in negative situations, expect low prices, and engage in extraordinary selling to minimize their losses, this results in undervalued prices of financial securities. This positive relationship between the sentiment of investors and returns does not exist over the periods because mispricing so caused does not persist for long periods and tends to revert to fundamental values with time, showing a negative relation.

The prevalence of optimistic and pessimistic investor sentiment in the equity market is an important factor and plays a heterogeneous role in influencing equity market prices. Daszyńska-Żygadło et al. (2014) observe a positive relationship between equity returns and a shift in optimistic investor sentiment. Investor sentiment may be direct (Yang et al., 2013) or indirect (Baker and Wurgler, 2007; Bathia and Bredin, 2013; Liston-Perez et al., 2018; Schmeling, 2009) relation to equity returns. An increase in the volume of trading reflects the optimistic behavior of investors, whereas a decrease in the value of trading volume exhibits the pessimistic behavior of investors (Chuang et al., 2010). Pessimistic investors avoid buying riskier assets to prevent their losses. As a result, trading volume in the market decreases (Rousseau et al., 2008). The sentiment of investors may be positive or negative towards the stocks, and the effect of each type differs in nature. Negative investor sentiment may have a positive influence, whereas positive investor sentiment may not affect equity returns (Huang et al., 2014). Similarly, negative sentiment indicators may be more effective in explaining stock returns than positive ones (Lv et al., 2022).

The influence of optimistic and pessimistic investor sentiments on equity returns may be symmetric or asymmetric. In several studies, the effect of optimistic investor sentiment on equity returns is found to be higher than the effect of pessimistic investor sentiment (Ding et al., 2004; Dong, 2020; Huang et al., 2014; Li, 2020; Zhang and Semmler, 2009) whereas, in some other studies the effect of pessimistic investor sentiment is found higher than the effect of optimistic investor sentiment (Dhaoui and Khraief, 2014; Paramanik and Singhal, 2020; Zheng, 2015; Fang et al., 2021). The asymmetric effect of investor sentiment is also visible for industrial returns (Chen et al., 2013) and stocks that are difficult to arbitrage (Smales, 2014). The relationship between market sentiment and excess equity returns is sometimes U-shaped, indicating that excess returns are associated with higher levels of positive (negative) sentiment, and the impact is greater, resulting in a significantly higher (lower) abnormal return (Dong, 2020).

As sentiment is a qualitative behavioral factor and there is no valid and reliable tool to measure it quantitatively, the researchers use a variety of measures to quantify this trait; therefore, quantification of the behavior of investors about the market remains challenging. Each measure used to gauge investor sentiment has its own merits and demerits, and no single agreed-upon measure is available for this purpose. A survey is a common tool that only captures short-term effects (Fisher and Statman, 2000). Some studies employ market-centered indicators such as trading activities and price movements for setting up the investor sentiment index. A single sentiment proxy that characterizes investor sentiment is a simple way to quantify it, but a few researchers doubt its validity and credibility (Brown and Cliff, 2004). Haritha and Rishad (2020) raise an objection to the use of a single proxy with the remarks that it is not enough to explain investor sentiment because several factors cause variations. There is no guarantee that a single sentiment measure includes all the relevant information regarding feelings. Currently, various proxies for quantifying market sentiment are easily available that fulfill the statistical requirements of the measure. Baker and Wurgler (2006) use six sentiment proxies, namely, (a) dividend premium, (b) closed-end fund discount, (c) equity share in new issues, (d) turnover rate, (e) average first-day returns on IPOs and (f) number of IPOs. IPOs are banned in China's stock market; therefore, Li (2020) uses the number of IPOs, average first-day returns, psychological line index, new stock accounts, and new fund accounts to represent the sentiment level in China's stock market.

Investor sentiment and equity returns may or may not have a linear relationship. Several studies focused on the linear relationship between investor sentiment and equity market returns (Dash and Mahakud, 2013; Karakatsani and Salmon, 2008; Wang et al., 2022; Zou and Sun, 2012). A positive (negative) shift in investor sentiment improves (decreases) equity returns during bull markets, whereas a negative (positive) shift in sentiment during bear regimes does the opposite (Wang et al., 2022). Baker and Stein (2004) find a negative relationship between investor sentiment and equity returns using trading volume as a proxy measure. For both individual and institutional investors, Verma and Verma (2007) reveals a strong positive relationship between investor sentiment and equities market returns. Another study carried out by Gebka and Wohar (2013) also reveals a positive relationship between equity returns and the volume of trading. The impact of institutional investor sentiment on equity market prices is only in the short run, and that sentiment is more prone to negative returns (Kling and Gao, 2008). Sometimes, it is observed that smaller, distressed, non-profitable, and riskier stocks earn higher returns during low-sentiment periods and vice versa (Baker and Wurgler, 2006), whereas difficult-to-value and arbitrage stocks have lower returns during bearish periods (Baker et al., 2012).

The focus of most of the earlier studies has been on finding the relationship of investor sentiment with equity returns in linear settings, but this relation is not always linear (Dergiades, 2012; Gebka and Wohar, 2013; He et al., 2020; Namouri et al., 2018; Ni et al., 2015; Xie, 2017) because various factors such as market conditions, economic trends, and investor behavior can influence this relationship. Nonlinear patterns observed in the series of financial data are mainly due to investor sentiment (Wang et al., 2013). When the markets are highly bullish, there are chances of bubbles in the market, leading to overpricing of assets and quick correction with negative returns. Likewise, during highly bearish market times, there are chances of crashes that lead to underpricing of assets and, ultimately, sharp recovery with positive returns. In the presence of such non-linear data patterns, traditional linear data analysis techniques may lead to erroneous results that are impossible to generalize. Therefore, in recent years non-linear (asymmetric) impact of investor sentiment on equity returns has become the focus of research.

A positive asymmetric relationship between the aggregate market returns and investor sentiment is observed in upper quintiles and negative at lower quantiles (Tuyon et al., 2016), positive in lower quintiles and negative in upper quintiles (Chakraborty and Subramaniam, 2020) is observed. When the sentiment of investors and market conditions are involved in the study, it provides (a) significant positive relation between optimistic investor sentiment and market returns under moderate market conditions and (b) significant negative relation between pessimistic investor sentiment and returns under all market conditions (He et al., 2020). Similarly, a positive relationship at higher quantiles during bullish market trends and negative relation at lower quantiles during bearish market trends is also observed (Gebka and Wohar, 2013). A significant asymmetric effect for pessimistic investors during bullish market conditions and insignificant for optimistic investors are observed when the contagion effect of investor sentiment is incorporated into the study (Tsai, 2017).

In behavioral finance, it is presumed that investor sentiment can be used as a predictor of stock market returns, so consideration of sentiments in predicting stock market returns has been the focus of debate for a long time. Many studies have investigated the forecasting power of investor sentiment using different proxies, methodologies, and frequencies of data in various markets. Many studies find sentiment as a powerful predictor of market returns, whereas, at the same time, many studies claim that investor sentiment is not a significant predictor of market returns (Baker et al., 2006; Baker and Wurgler, 2007; Brown and Cliff, 2004, 2005; Kadilli, 2015; Kim et al., 2014; Kim and Kim, 2014). A vast body of literature stresses the link between investor sentiment and market returns in a temporal context. Some find investor sentiment a significant predictor of stock market returns in the short term (Zhao et al., 2009); others find it is significant in the long term (Liston-Perez et al., 2018). On the other side, Brown and Cliff (2004, 2005) and Yelamanchili et al. (2019) find investor sentiment as an insignificant predictor of stock market returns in the short term, while Kling and Gao (2008) find investor sentiment as an insignificant factor even in the long term.

Similarly, mixed results are observed when the direction of the relationship between investor sentiment and its predictive power is studied. Huang et al. (2014) observe a negative relationship in the short term, whereas Cheema et al. (2020b) report a positive link in the short term. Ruan et al. (2020) report a negative link in the long term, whereas Brown and Cliff (2004, 2005) find a positive impact in the long term. The controversy observed in the results is attributed to the non-linearity inherent in data (Bekiros et al., 2016), measurement method (Huang et al., 2015) statistical techniques (Balcilar et al., 2018), structural properties of data (Agarwal and Vats, 2021) and difference in market cultures. (Nishiyama et al., 2011). Wang (2021) are the first to notice the existence of non-linearity between two variables. Bekiros et al. (2016), using S^{BW} and S^{PLS} indices, find no relationship between investor sentiment and market returns under non-linear conditions. This study concludes that non-linearity in the data must be considered in generalizing the results. Wang et al. (2018), while using the nonlinear Granger Causality Model, confirm the non-linear relationship between investor sentiment and stock market returns. Balcilar et al. (2018), using the nonparametric Granger Causality Quintile Test and S^{BW} and S^{PLS} indices, find that investor sentiment can predict stock market price returns in a nonlinear fashion.

Investor sentiment may be categorized into extremely high level and extremely low level (Sheu et al., 2009), extremely bright and extremely dark (Liu et al., 2011), moderate, optimistic, and overly optimistic (Namouri et al., 2018), moderate, extremely optimistic, and extremely pessimistic (Li, 2020) and these categories can be used as leading indicators of market returns. During periods of extreme optimism, investors become over-enthusiastic and invest eagerly without assessing the fair value of the financial securities, which results in market bubbles, where asset prices become overvalued. Conversely, during periods of extreme pessimism, investors become excessively fearful regarding the financial markets, sell off their riskier assets, and invest in risk-free assets, which results in market crashes, where asset prices become significantly undervalued. Investor sentiment has a heterogeneous effect on market returns: moderate has a predominant effect, optimistic has a positive and more activated effect, and overly optimistic has a reversal effect (Namouri et al., 2018). Moderate investor sentiment has a positive correlation whereas extremely optimistic and extremely pessimistic investor sentiment has a negative correlation with equity returns (Li, 2020). Extreme optimism and extreme pessimism can smoothly switch the market from bullish to bearish and bearish to bullish states, depending on the heterogeneous responses of the market participants and the investors' risk appetite (Dahmene et al., 2021).

Investor sentiment is important in generating conditional volatility in the equity market (Baker and Wurgler, 2006; Liston and Huerta, 2012). Conditional volatility refers to the phenomenon where the volatility of stock returns varies over time and depends on the level of some underlying variable, such as investor sentiment. Bullish investor sentiment makes the investors buy riskier assets enthusiastically without assessing their fair value resulting in higher volatility in the equity market. In contrast, bearish investor sentiment makes the investors more risk averse, and they sell their riskier assets resulting in low volatility in the market. Negative sentiment scores prove better predictors of liquidity and volatility in the equity market (Gakhar and Kundlia, 2021). The relationship between investor sentiment and conditional volatility is not always the same; sometimes, extremely optimistic sentiment causes market bubbles, and sometimes, extremely pessimistic sentiment creates a sharp decline in the market due to the pressure of selling; both situations lead to an increase in volatility. This relationship of investor sentiment with return volatility may be long-term (Suresh and George, 2016) or short-term and reversed in the following week (Aziz and Ansari, 2021). Investor sentiment had an asymmetric effect on volatility during moderate, strong troughs and peaks of sentiment periods (Nogueira Reis and Pinho, 2021). Investor sentiment is not the only reason for stock market volatility; it may be created by the shock of any nature to the stock market returns (Hu et al., 2021).

The relationship between stock returns and market risk has long been the research focus in finance. Accurate risk measurement has been a concern for researchers, and several methods have been introduced. One of the most used methods is Value at Risk, introduced by Morgan/Reuters (1996). This single number calculates the potential risk arising from many causes. This method evaluates the expected loss of stock returns in a specific period at some probability level. Another method introduced by Artzner et al. (1999) is an expected shortfall (ES) or conditional value at risk (CVaR). It quantifies the portfolio risk at a specific confidence level and represents the expected loss greater than the VaR during a holding period. Usually, the relationship of VaR with equity returns is positive (Bali and Cakici, 2004), but it may be negative (Shaikh, 2018); this unusual behavior of VaR with equity returns are attributed to investor sentiment. Different levels of investor sentiment have a varied influence on the relationship of VaR with returns. During spans of high investor sentiment, VaR has a negative relation with the expected stock return (Bi and Zhu, 2020; Wang et al., 2020). This investigation is supported by the prospect theory of Tversky and Kahneman (1992) and Kahneman and Tversky (1979).

The list of factors affecting the equity returns, discussed earlier is not complete; many other macroeconomic factors (Term Spread, Gross Domestic Product, Industrial Production Index and Risk Free Rate) have impact on the association of investor sentiment with equity returns. A higher risk-free rate may lead to lower equity returns due to investors' preference for safe investments (Balcilar et al., 2015). Conversely, a low risk-free rate may lead to lower returns due to their preference toward riskier equities. Industrial Production Index is associated with higher equity returns because its higher value indicates that the economy is growing, which boosts the sentiments of investors that result in higher equity returns. Similarly, its lower value indicates that the economy is declining, which bumps investors' sentiments and results in lower equity returns (Sahu et al., 2020). Term Spread is also associated with higher equity returns as investors are optimistic about the future demand for equities becoming higher, resulting in higher equity returns (Viceira, 2012). However, high macro-risk hedge funds may generate higher returns following low-sentiment months, while the risk-return relationship is flat following high-sentiment months. It means that standard asset pricing theory applies when market participants are rational, but sentiment-induced mispricing affects hedge funds with high macro-risk loadings. When the influence of macroeconomic variables on stock return is studied, taking industrial production, long-term interest rates, consumer price index, and money supply, a significant positive relationship between industrial production and stock return, a negative relationship with long term interest rate and money supply and insignificant result with money supply is observed for the US market which may vary with change in the market.

Investor sentiment index remains effective in explaining the equity returns during the COVID-19 outbreak; on the one side, it causes huge losses in the equity market, and on the other, it creates opportunities for recoveries and huge gains (Reis and Pinho, 2021). This influence of COVID is due to the anxiety that produces a pessimistic feeling that influences investment decisions and asset returns. Pessimistic investors are more cautious about potential returns, so they take fewer risks, resulting in lower returns (Kaplanski and Levy, 2010). The negative effect of COVID-19 on investor sentiment and equity returns (Liu et al., 2020b; Yahya et al., 2021; Zhai et al., 2022), as well as the positive effect (Liu et al., 2020a), is observed.

1.1 Theoretical Background

According to modern financial theory, irrational traders exist in the stock market. When these traders make transactions based on their personal feelings, sentiment, and incorrect and incomplete information, they are called 'Noise Traders,' and the phenomenon is called 'Noise Trading.' The impact of noise trading on the market prices is called 'Noise.' Many of the latest studies believe that irrational traders have a small and short-term impact on stock prices, either because of the noise of traders' counter actions or smart traders' interventions.

It is claimed that rational investors are not always so powerful to remove the noise in the market, due to which volatility and liquidity exist, which creates an opportunity for irrational investors to trade and prevent the rational trader from betting against them. Such trading made by irrational investors creates mispricing in the market, which in turn creates space for noise traders to trade in the market and remain there for longer periods (Black, 1986). In this way, noise traders play a vital role in keeping the prices away from their fair values (Shefrin and Statman, 1994).

Prospect theory, also called loss aversion theory, suggests that emotionally the investors do not give equal weightage to gain and loss of the same magnitude. They feel more aggrieved and pain from a loss as compared to they feel pleasure from a gain. Therefore, the investors become more risk-avoiding than proposed by traditional finance theory. Resultantly, this risk-avoiding attitude affects the trading of riskier assets.

It is evident from the empirical studies that investor sentiment is linked with their perceived risk, and this relationship is consistent with the prospect theory. It is observed that during spans of high sentiment, investors become overconfident, exhibit risk-seeking behavior, and perceive less risky assets (Kim and Lee, 2022). In contrast, during spans of low sentiment, investors become more loss-averse and exhibit risk-averse behavior, perceive risk more than actual, and avoid buying riskier assets (Hong and Stein, 1999).

1.2 Gap Analysis

In the studies of the linear relationship between investor sentiment and stock return, both positive (Anusakumar et al., 2017; Li and Zhang, 2008; Sayim and Rahman, 2015) and negative (Bujang et al., 2015) relationship is observed. Similarly, in non-linear relationship studies, negative and positive correlations are found (Ni et al., 2015). These differences in the results require a comprehensive study to determine whether the relationship between investor sentiment and returns is non-linear and positive or otherwise.

There is a considerable body of knowledge arguing that investor sentiment is not a significant predictor of returns (Baker and Wurgler, 2006, 2007; Brown and Cliff, 2004, 2005; Kadilli, 2015; Kim and Kim, 2014) but on the other hand, many studies find sentiment as a powerful predictor of market returns. Some find investor sentiment is a significant predictor of stock market returns only in the short term (Yumei and Mingzhao, 2009), while others find it significant only in the long term

(Liston and Huerta, 2012). These contrasting findings demand an investigation to find the predictive power of investor sentiment for stock return regarding duration.

Optimistic and pessimistic investor sentiment have symmetrical and asymmetrical influences on stock market returns. In several studies, the effect of optimistic investor sentiment on equity returns is found to be higher than the effect of pessimistic investor sentiment (Ding et al., 2004; Dong, 2020; Huang et al., 2014; Li, 2020; Zhang and Semmler, 2009) whereas, in some other studies (Dhaoui and Khraief, 2014; Paramanik and Singhal, 2020; Zheng, 2015) the effect of pessimistic investor sentiment is found higher than the effect of optimistic investor sentiment. Therefore, the nature of the relationship needs to be studied in detail.

There are few studies in which the influence of extreme levels of investor sentiment on equity returns has been explored. The studies carried out in this context have not concluded consistent results. Some studies find a positive (Barberis, 1998; Stambaugh et al., 2014; Liu et al., 2020b) relationship between an extreme level of investor sentiment with equity returns, while others find it negative (Liu et al., 2011; Namouri et al., 2018); therefore, further research is required to certain the relationship.

Despite the availability of huge body of literature discussing the effect of investor sentiment on volatility, there is a lack of consensus on the direction and magnitude of this relationship. Some studies find that higher levels of investor sentiment lead to higher volatility (Sadaqat and Butt, 2016; Shen et al., 2017; Yu and Yuan, 2011), while others find low volatility (Lee et al., 2002; Li and Zhang, 2008; Wang et al., 2022). Likewise, some studies find that low levels of investor sentiment increase volatility (Lee et al., 2002; Li and Zhang, 2008), while others find decreases in volatility (Sadaqat and Butt, 2016). Therefore, there is a need further study the way investor sentiment influences volatility.

Negative correlation is observed between VaR and equity returns (Chen and Chiang, 2016), which is in contradiction with the results of previous studies wherein a positive relationship is observed between VaR and equity returns (Bali and Cakici, 2004). It is thought that investor sentiment is responsible for this changed behavior. Therefore, some studies have been conducted to find the relationship between VaR and expected return under different sentiment levels (Bi and Zhu, 2020), but their results remain inconclusive. This situation invites the researchers to validate the findings by expanding the study.

While testing the relationship between the level of investor sentiment and stock return, some studies (Baariu and Jagongo, 2022; Jelilov et al., 2020; Kim and Ryu, 2020) used the macroeconomic variables as an explanatory variable because it directly influences stock return under diverse levels of investor sentiment. In contrast, some studies have used macroeconomic variables as moderating variables. Therefore, there is a need to re-examine how is the association of investor sentiment with equity return respond to various macroeconomic factors.

COVID-19, on the one side, results in huge losses (Goel and Dash, 2022; Hamal and Gautam, 2021; Huerta and Perez-Liston, 2010; Subramaniam and Chakraborty, 2021) to stock markets and, on the other side, creates opportunities for recoveries and huge gains (Reis and Pinho, 2021; Yahya et al., 2021). COVID-19 is a global pandemic, and its effects on the economies vary. So, this study needs further investigation to explore the effect of investor sentiment on equity returns in this epidemic situation in different markets.

1.3 Problem Statement

The stock markets are influenced by both rational as well as irrational investors. The irrational investors take investment decisions on the basis of their sentiments, and are responsible for deviation of prices, in the market, from their intrinsic value. As compared to developed stock markets, the fluctuation of prices is more common in emerging stock markets, because these markets have a larger number of irrational investors and so more suitable for the study of sentiment. This indicates that abandoning the irrational investor sentiment paradigm may be premature.

1.4 Research Questions

- What type of relationship exists between investor sentiment and stock returns?

- Is investor sentiment able to forecast the stock market returns in the short and long run?
- Whether bullish and bearish investor sentiments influence equity market returns in a similar fashion?
- Do equity markets respond to extremely optimistic and extremely pessimistic investor sentiments in a similar way?
- Do bullish and bearish investor sentiments affect conditional volatility in a similar fashion?
- Do positive and negative investor sentiments affect the linkage between market risk and stock returns?
- Does the relationship between different states of investor sentiment and equity returns vary with changes in the macroeconomic environment?
- Does the pandemic (Covid-19) influence the relationship between investor sentiment and stock return?

1.5 Objectives of the Study

This study aims to:

- Examine the non-linear relationship between investor sentiment and contemporaneous equity returns.
- Investigate the predictive power of investor sentiment for equity returns in the short and long run.
- Evaluate the impact of positive and negative investor sentiments on equity returns.
- Assess the effect of extreme levels of optimistic and pessimistic investor sentiments on equity returns.

- Identify the non-linear relationship of bullish and bearish investor sentiment on conditional volatility.
- Examine the impact of different levels of investor sentiment on the relationship between market risk and equity returns.
- Determine the influence of change in the macroeconomic environment on the relationship between different states of investor sentiment and equity returns.
- Analyse the relationship between investor sentiment and equity returns during the pandemic (COVID-19).

1.6 Significance of the Study

The trading behavior of investors in emerging economies is more irrational than that of developed economies because investors in these markets do not make rational decisions, and their sentiments dominate their decisions, resulting in reduced efficiency of the equity market. The present study is conducted in emerging equity markets, including BRIICS plus Pakistan, to provide valuable insights into market movements, investment decisions, and overall economic conditions. This information is valuable for investors in making informed decisions and mitigating the risks associated with volatile and unpredictable markets.

- The investigation findings supplement the body of knowledge and help the researchers to understand the market concepts in a better way. They can understand the relationship among various variables more clearly. They can expand the research based on the findings of this study.
- This study may help policymakers, company managers, and stock market administrators to understand the role of different levels of investor sentiment that are key drivers for price fluctuations in the stock market and will be able to devise strategies to manage the stock fluctuations in a better way.
- This study may facilitate investors to make systematic predictions, devise appropriate strategies in choosing their portfolios leading to high returns, and move the markets toward efficiency.

1.7 Organization of the Study

The organization of the study includes an abstract, introduction, literature review, methodology, results, discussions, summary and conclusions, and references.

Introduction; includes an overview of the research topic, gaps, questions, objectives, and significance. Literature Review; section provides a detailed review of the existing literature on the topic, highlighting the key findings and limitations of previous research and hypotheses of the study being addressed in the study. Methodology; section includes a description of the study population, sample selection, sources of data collection, and econometric models. Results and discussion; section presents the study's findings, using tables and descriptive statistics to illustrate the data. It also includes a discussion of the main results. Conclusion; This section includes a summary of the main findings, future recommendations, specific recommendations, limitations, and future directions of the study. References section; includes a comprehensive list of all the references cited in the thesis.

Chapter 2

Literature Review

This chapter provides a detailed review of the existing literature relevant to the topic, highlighting findings and limitations of the studies and construction of hypotheses to be tested in the present study.

2.1 Traditional and Behavioral Asset Pricing Models

When traditional models of asset pricing failed to fully explain and predict the market returns, then investor sentiment attracted the attention of the researchers, and they tried to link market behavior with investor sentiment. Xu and Green (2013) studied the impact of normal and positive investor sentiment on Chinese stock returns using a three-factor Fama and French (1996) model as a benchmark and observed that when factors were conditioned by the sentiment, this traditional model was found less significant, suggesting that in China, investor sentiment affects portfolio returns. Yang and Zhou (2015) examined the role of investor sentiment and investor trading behavior on asset prices and found that both significantly affect excess returns beyond the three-factor model of Fama and French.

Yu (2021) studied Fama-French factors in combination with investor sentiment (measured by a six-variable composite index) and developed a new multiple-factor asset pricing model to analyze its impacts on the U.S. monthly equity returns and observed that the Fama-French three-factor model, when combined with investor sentiment factor fully explained the U.S. equity market returns. Habibah et al. (2021) added investor sentiment as an additional factor to Fama & French five-factor model and, by applying the Vector Auto Regression and Granger Causality Tests, analyzed the effect of sentiment on five-factor premium and vice versa and concluded that investor sentiment encompasses some information to explain the Fama-French five-factor premium, especially investment premium, size premium, and profitability premium. Size premium and market risk premium increased during low sentiment spans (a negative relationship), whereas investment premium, profitability premium, and value premium increased during high sentiment spans (a positive relationship).

Wu et al. (2016) synergized the Fama and French 3-factor model with investor sentiment and applied the Panel Smooth Transition Regression framework to explore the nonlinear and heterogeneous effect of investor sentiment on the risk premiums of companies in Taiwan and found that extreme optimism or extreme pessimism decreased the market premiums and these premiums in 'holding growth stocks' dominated the 'holding value stocks' under extreme sentiments. Furthermore, an increase in the volatility index (investor sentiment) decreased the size premium, and value stocks earned more returns than growth stocks under normal sentiments. Goh et al. (2018) augmented Fama and French three-factor model with market-wide investor sentiment and applied the Markov Regime-Switching framework in Bursa, Malaysia, for observing two regime-switching patterns in nonlinear settings. The results showed that a shift in investor sentiment had significant predictive power in switching the regime dynamics between the Malaysian bull and bear market. During bear markets, the positive sentiment of investors had a greater transition probability of regime switching. Furthermore, the market premium fell when the stock market switched from bull to bear markets, whereas value and size premiums increased. Rashid et al. (2019) studied the indirect and direct effect of the Fama and French 3 Factor Model and the Carhart 4 Factor Model in combination with investor sentiment on the monthly returns of Pakistani companies. They observed that both models had a positive and significant direct effect on returns. However, when the relation was studied indirectly, the investor sentiment had a negative effect on the size, value, and risk premiums, and the momentum effect was positive for size and market risk premium but negative for the value premium. The predictive power of the Fama and French 3 Factor Model and the Carhart 4 Factor Model was improved when the sentiment factor was included. Swamy et al. (2019) proved that when the Fama-French four-factor model and Google Search Volume Index were used collectively, they better explained the excess returns in both direction and magnitude compared to the model without Google Search Volume Index. Li (2020) claimed that the sentimental-based factor model was more explanatory than the fundamental three-factor model of Fama and French in explaining the Chinese market equity returns. Rehman et al. (2020) analyzed the prediction of sectoral and aggregate returns in the US market by using the sentiment index of Baker & Wurgler's, bullish as well as bearish investor sentiment indices of the American Association of Individual Investors, and various risk indices and proved that investor sentiment was a poor predictor when used solely, but when used in combination with risk factors its predictive power became more accurate.

To examine the impact of heterogeneous individual investor sentiment on excess equity returns at various time terms, Li (2020) constructed two indices, namely the 'market-based sentiment index' and 'stock-specific sentiment index' using panel data at various frequencies of time in the Chinese stock market and found a significant relationship between stock specific sentiment and excess market returns at quarterly, monthly and weekly periods. The effect of sentiment-based trading that was prominent in the beginning gradually decreased over time. Li claimed his sentimental-based factor model is more explanatory than the fundamental three-factor model of Fama and French.

Chen et al. (2022) found that lower turnover stocks in the Chinese equity stock market generated higher future returns than higher turnover stocks, even after controlling for liquidity measures and existing traditional asset-pricing models. The effect was stronger during periods of high sentiment and for stocks with lower institutional ownership, investor sophistication, transaction costs, and idiosyncratic volatility. The investor sentiment index constructed based on big data and social networks by Tianyu (2019) was used in studying the role of investor sentiment on equity returns and proved this investor sentiment index as the best predictor. When used in combination with the traditional model of Fama and French (3 factors), this sentiment index showed better results in explaining the market returns.

2.2 Investor Sentiment and Contemporaneous Market Returns

Daszyńska-Żygadło et al. (2014) conducted a study on 8 emerging markets by analyzing media coverage-based text data and created an optimism index 'Thomson Reuters Market Psych Index' to evaluate its effect on contemporaneous aggregate returns. In 2 countries positive relationship was observed, and returns in 4 of the 8 selected emerging markets were more vulnerable to negative sentiments of investors. Nasiri et al. (2019) conduct a study of the Tehran Stock Exchange based on document mining referrals and repeated the role of investor sentiment on asset pricing. Phuong (2020), by using Psychological Line Index as a proxy to measure investor sentiment and applying Fama-Mac-Beth and General Least Squares regression analyses, examined 57 Ho Chi Minh City stock exchange companies and observed a significant impact of investor sentiment on equity market returns. Aggarwal and Mohanty (2018) applied Principal Component Analysis on indirect market measures and macro factors of Indian and US markets to develop a sentiment index, used it to analyze its impact on contemporaneous stock returns, and found a significant positive relationship between the sentiment index and equity returns.

Taking internet search volume data from Google trends, Beer et al. (2013a) created an investor sentiment index for the French mutual fund market and found that current returns of mutual funds were affected by investor sentiment. Hu and Sun (2021) applied Principle Component analysis on five selected emotional proxy variables to construct a composite investor sentiment index and used the MS-VAR model to determine the relationship between investor sentiment and equity returns. In the bullish market, the shock to investor sentiment significantly impacted stock market returns. Zhang and Semmler (2009) studied the influence of investor sentiment on A and B-type shares traded in Shanghai and Shenzhen Stock Exchange markets and found that returns of B-type shares moved following the global market in the absence of local investors, but this relation became insignificant with the entry of local investors. Phan et al. (2021) used a sentiment index created through principal components analysis to explore the impact of investor behavior on the Vietnamese equity market and observed a negative association between investor behavior and contemporaneous market return. Bu (2021) compared direct and indirect measures of investor sentiment and observed that direct measures of sentiment significantly affect current equity returns, but indirect measures have a more significant impact on previous returns. However, indirect measures have higher predictive power than that direct measures. Bu and Pi (2014) constructed an indirect measure of investor sentiment using lagging and leading variables in the Chinese market and found that an indirect sentiment index can be created using leading variables. The study also confirmed this sentiment index as a good predictor of equity returns. Bu (2021) found a low correlation between direct and indirect sentiment measures. Direct measures proved better in explaining the current returns, whereas indirect measures proved better in explaining the lagging effects. A strong synergistic effect was observed when both measures were combined. Further, indirect measures had higher predictive power for future returns and were influenced by short-term interest rates, while direct measures were driven by stock returns.

2.3 Persistency in the Nature of Investor Sentiment and Equity Returns relationship

Wang et al. (2020) examined stock comments from East Money and developed a sentiment classifier using LSTM to investigate the influence of the sentiment of online investors on the CSI300 equity transactions and found a significant positive impact on equity returns, trading volume, and big trade order imbalances. Emmanuel and Ahmed (2020) investigated the impact of 5 individual investor sentiment predictors on Nigerian equity market returns using multiple regression techniques and found a positive correlation between shifts in sentiment predictors and Nigerian equity market returns for some of the selected variables. However, the arbitrage conditions intensified the influence. In a Korean market, Yang et al. (2017) confirmed a positive and signification relationship between investor sentiment and asset returns by explaining that high stock market returns were induced by the high level of investor sentiment.

Liston and Huerta (2012) by applying the GARCH-in-Mean model, studied the way investor sentiment affects excess portfolio returns in the Mexican stock market and found that positive changes in investor sentiment led to higher excess returns of large, medium, and small-cap portfolios. Rahman et al. (2013) conducted a study in the frontier market of Bangladesh and applied the GARCH-in-Mean model and examined the role of noise traders in predicting excess returns, and revealed a significant and positive relationship between shifts in noise trader's sentiment and excess future equity market returns. It was further evidenced that a change in the magnitude of bullish and bearish investor sentiment indirectly affected returns through an asymmetric effect on volatility. In Saudi Arabian Stock exchange market, Altuwaijri (2016) used volume and liquidity data as a proxy measure of investor sentiment and found its positive relation with aggregate equity market returns.

Musembi (2020) investigated the impact of investor sentiment on the Kenyan equity market performance using monthly secondary data obtained from various sources and analyzing it using ARDL and NARDL models and found a significant positive relationship between investor sentiment and the Kenyan equity market performance. Therefore, the study recommended that the Capital Markets Authority closely monitor investor sentiment changes as it significantly affects the equity market's performance. Verma et al. (2008) analyzed the impact of irrational and rational investor sentiments on the S&P 500 returns. They found that rational sentiments had a greater impact on stock market returns than irrational sentiments, while there were immediate positive responses to irrational sentiments, which were corrected by negative responses in the subsequent periods. Additionally, the study found that past stock market returns positively affected irrational sentiments without impacting rational sentiments. The study's results supported the idea that stock returns are driven by economic fundamentals but also provided evidence in favor of the role of investor sentiment in determining stock returns.

In a study by Aziz and Ansari (2021), a positive association between expected equity prices and Google searches of Indian companies was found. The study also revealed that market sentiment was moderated by linking expected equity returns with Google searches. Da et al. (2015) investigated the potential of online ticker searches in predicting excess equity returns and trading volumes proving such searches as valid proxies for investor sentiment, particularly among less sophisticated and retail investors. Hsu and Liao (2016) used a text mining technology termed the "Sentiment Analyzer system" on the posts collected from The 'M Fool' financial website to examine the impact of investor psychology on equity returns at various time terms under information uncertainty. A positive relationship between investor sentiment and weekly returns was observed, and this relationship was influenced by uncertain information in the short run also.

2.4 Reversal effect in the Nature of Investor Sentiment and Market Returns relationship

According to Cosemans and Frehen (2021), investors expect the continuation of the past positive gains in the future; hence they invest in overvalued assets that result in lower returns subsequently and vice versa. Yoshinaga and de Castro Junior (2012) conducted a study in the Brazilian market and constructed a sentiment index employing Principal Component Analysis by classifying firms into quantiles based on age, risk, and market value, and average returns were calculated at each quantile based on the sentiment index of the previous quarter. Results showed a significant and negative relationship between the sentiment index and future rates of return, reflecting a reversion pattern in stock returns. A positive sentiment period led to lower returns for smaller, riskier, and younger firms, whereas a negative sentiment period led to higher returns. Aissia (2016) used an index created by Baker and Wurgler (2006), selected Closed-End Fund Discount to measure investors' sentiment, and found a negative relationship between the sentiment of both local and foreign investors with future equity returns. Bathia and Bredin (2013) used various proxies to assess investor sentiment and examined the significant negative role of investor sentiment on equity returns that gradually decreased with time, especially beyond one month.

Fisher and Statman (2000) found that sentiment varies among different types of investors, with no correlation between Wall Street strategist's sentiment and individual investor sentiment or newsletter writer's sentiment. However, the sentiment was useful for strategic asset allocation, and there was a negative and significant relationship between sentiment and future stock returns for Wall Street strategists' sentiment and individual investor sentiment. Fisher and Statman (2003) by using data from the University of Michigan and the Conference Board examined the relationship of consumer confidence with equity returns and investor sentiment and found that consumers' confidence increased with high equity market returns. Still, high consumer confidence led to lower returns. While considering the economy, a positive association between individual investor sentiment and market returns was observed, while changes in the sentiments had no relationship with institutional investors and consumer confidence. In another study, Fisher and Statman (2006) observed that consumer confidence tended to increase when investor sentiment was positive but decreased when stock prices declined. However, low consumer confidence was more likely to be followed by high than low stock returns. Brown and Cliff (2005) found that investor sentiment, as measured by survey data, negatively affected asset valuation and future returns over multiyear horizons.

Baker et al. (2012) created investor sentiment indexes for six major stock markets and found that global and local sentiments were contrarian predictors of future market returns. The high sentiment was linked to low future returns on certain categories of difficult-to-arbitrage and difficult-to-value stocks. It was also indicated that sentiment was contagious across markets. Dalika and Seetharam (2015) created an aggregate investor sentiment index taking multiple proxies to analyze its impact on the South African market and observed a significant negative impact on returns. The low sentiment was linked to subsequent high returns of younger, smaller, extreme growth stocks and high volatility stocks. In contrast, the high sentiment was associated with reversing these patterns. An increase of one standard deviation in sentiment reduced future monthly returns by 0.198 standard deviations (Gric et al., 2021). Yang et al. (2017) used an indirect measure of investor sentiment by employing the VAR model and found a negative relationship between investor sentiment and future returns in the Tunisian stock market. Da et al. (2010) constructed a Financial and Economic Attitudes Revealed by Search (FEARS) index by aggregating online search queries related to depression, bankruptcy, and recession. Their study found that the FEARS index was correlated with low market returns on the same day but predicted high returns on the following day, indicating temporary mispricing due to sentiment. This effect was strongest among sentiment-favored stocks that were difficult to arbitrage.

Cheema et al. (2018) using indices developed by Baker and Wurgler (2006) and Huang et al. (2014) and applying a Two State Predictive Regression model observed that investor sentiment indexes were contrarian predictors of aggregate stock market returns at all-time horizons only during high sentiment spans. Jokar et al. (2018) aimed to investigate the impact of behavioral variables, such as herding behavior, management overconfidence, and the emotional tendency of investors on stock returns in the Iran Stock Exchange utilizing a panel dataset and a multiple linear regression model to analyze the data. Results indicated that the studied behavioral variables had a significant and inverse effect on the stock returns of companies.

Yang et al. (2013) developed a sentiment asset pricing model and analyzed the impact of investor sentiment on asset pricing by examining the negative expected returns under varying parameter conditions. The study presented an overlapping asset pricing model and concluded that investor sentiment led to a negative expected return. Erdemlioglu and Joliet (2019) examined the impact of sentiment on long-term optimal equity portfolios, particularly in European stocks, and found that sentiment had a significant negative association with contemporaneous excess returns of semi-active strategies, especially during bullish periods, while its impact on the passive portfolios was negligible. Cheema and Nartea (2017) found that investor sentiment was predictive of cross-sectional returns, particularly for difficult-to-value stocks, which were often overpriced during high sentiment periods. However, the predictability of subsequent lower returns for these stocks occurred when subsequent investor sentiment decreased, whereas they earned relatively higher returns following high sentiment periods. Da et al. (2010) found that irrational factors influenced the Consumer Confidence Index and the European Union (EU) Economic Sentiment Indicator, which were negatively related to Portuguese equity returns. Sentiment predicted overall market returns but not all of the industrial index returns, and there was no impact of US investor sentiment on the market returns of Portugal.

It was observed that sentiment had a greater impact on securities with limited arbitrage opportunities and subjective valuations. Low sentiment correlated with subsequent high returns for extreme growth, non-profitable highly volatile, young, not-dividend-paying, small, and distressed stocks, whereas, high sentiment resulted in subsequent low returns for these categories of stock (Chen et al., 2009; Wang et al., 2007). Dimpfl and Kleiman (2019) examined the relationship between German retail investor sentiment and market returns by creating four pessimism indices based on Google search queries and found that changes in sentiment were highly predictive of market returns, trading volume, and volatility. Increased pessimism led to lower contemporaneous returns and higher trading volume and volatility but higher future returns and lower future trading volume and volatility. These results supported the idea of correction effects and were consistent with modern sentiment theory.

Based on survey data, Brown and Cliff (2005) investigated the relationship between asset valuation and investor sentiment and found that high levels of sentiment led to mispricing and lower future returns over multiyear horizons, and this relationship was not affected by the inclusion of other known variables used to forecast stock returns. Lin and Qiu (2023) studied the relationship between sentiment beta and stock returns in China's stock market and found that stocks with low sentiment beta outperformed compared to those with high sentiment beta. An 'Against Minus Catering' sentiment (AMC) was identified as a pricing factor that strengthened the negative relationship between sentiment beta and stock returns for highly subjective valuations stocks. The strength of this relationship varied based on the level of arbitrage restrictions. Chughtai et al. (2017) conducted a study and examined the effect of investor sentiment on stock returns in various industrial sectors of Pakistan. They used Principal Component Analysis to construct industry-level sentiment indices and found that overall investor sentiment negatively affected both current and future stock returns in the country, suggesting that mispricing persisted over time due to investors' overreaction to the available information. These findings indicated that stock markets were not fully efficient in adjusting instantaneously.

Bathia et al. (2016) studied the relationship of investor sentiment with G7 equity market returns using various proxies, including equity fund flow, put-call ratio, surveys on investors, equity, and closed-end fund discount, and found a contrarian relationship between sentiment and expected returns, with value stocks being particularly affected. The current equity fund flow was considered responsible for price pressure on value stocks. Further, an increase in value stocks and a decrease in growth stocks was associated with closed-end fund discount. Miwa (2016) found that under spans of bullish investor sentiment, overestimation in the growth of some specific stocks resulted in high levels of mispricing, which subsequently resulted in lower earnings over time. Cheema and Nartea (2017), by examining the mispricing of safe and speculative stocks concerning sentiment dynamics, found investor sentiment as a contrarian predictor for equity returns. Sentiment-driven exacerbated and continued mispricing was corrected with sentiment transitions. Cheema et al. (2018) used a Two-State Predictive Regression model to investigate the predictive effect of low or high investor sentiment on equity returns and provided evidence that this predictability was limited during high sentiment periods only because overpricing was more affected than underpricing. Dalika and Seetharam (2015) created an aggregate investor sentiment index using various proxies to investigate its relation with South African equity market returns and found that when sentiment was low, stocks like extreme growth, smaller, young, and high volatility stocks showed higher subsequent returns. Conversely, when sentiment was high, these patterns reversed, suggesting that investor sentiment strongly influenced share returns in South Africa.

Sui (2021) developed a dynamic equilibrium model to connect mispricing with investor sentiment, finding that when investors extrapolated past returns, they mispriced the assets, resulting in predicted lower future market returns. However, when their wealth level was low, high investor sentiment predicted high future returns due to price correction. This model matched investor sentiment in surveys and patterns of boom-bust cycles in the stock market.

Wang (2021) studied 50 global stock markets to analyze the relationship between the consumer confidence index (CCI) and expected equity returns and found a negative relationship between sentiment and future stock returns globally. Emerging markets showed a more immediate impact, and developed markets demonstrated a long-lasting effect. The study also revealed cross-market differences in the sentiment-return relationship, which could be attributed to differences in investors' education, participation level, intelligence, culture, and professional growth. Lansing et al. (2022) repeated that higher noise predicts lower excess stock returns. Santana et al. (2020) examined the impact of individual stock investor sentiment on the management of earnings by Brazilian firms and found a positive relationship between stock sentiment and earning manipulations, which was contrary to previous findings on market sentiment in North America. This study concluded that managers were less likely to manipulate earnings in response to known losses in the Brazilian capital market.

2.5 No Link of Investor Sentiment with Market Equity Returns

Fisher and Statman (2003) found no relationship between changes in the sentiments of institutional investors and consumer confidence. Kling and Gao (2008) did not find any predictive power of investor sentiment for future market returns in the long term, however, found a positive link in the short run.

Finter et al. (2012) constructed a sentiment indicator through a Principal Component Analysis to examine the effect of sentiment indicators on the German stock market returns. It was noticed that some stocks were sensitive to sentiments while others were not. However, there was limited predictive power of the sentiment for future stock returns, and this was presumed due to the low fraction of retail investors in the German market.

Mathur and Rastogi (2018) developed an investor sentiment index for India to investigate its association with stock returns and found that while the sentiment index did not predict broad market returns, it was inversely related to the subsequent year's returns of small, low-priced stocks. Kim and Kim (2014) conducted a study using more than 32 million messages related to 91 firms from Yahoo Finance message board and found no evidence of prediction of future stock returns and volatility expressed in posted messages.

Gizelis and Chowdhury (2016) investigated the correlation between investor sentiment and equity market returns in the Athens Stock Exchange, using direct and indirect sentiment measures and found a weak connection between investor sentiment and returns, indicating the need to consider behavioral factors in asset pricing models for the Greek market.

The study also suggested that sentiment risk needs to be priced because it is not diversifiable. Xia and Guo (2015) studied the irrationality of the valuing stock appraisal system in the Growth Enterprise Market (GEM) and its impact on price determination and asset transactions.

Findings revealed that there was no long-term correlation between investor sentiment and equity returns in GEM. Although past market returns had a short-term effect on investor sentiment, they did not influence short-term stock returns. Investor sentiment affected market fluctuations, but market fluctuations did not significantly impact investor sentiment.

Salhin et al. (2016) investigated the impact of managerial and consumer sentiment indicators on UK sectoral returns using monthly data and found that consumer confidence was not a predictor of equity returns. In contrast, managerial sentiment had a significant impact on the aggregate market and sectoral returns. The study also revealed that the sentiment-return relationship differed over sectors and was dominated by sentiment associated with manufacturing firms.

In the Chinese stock market, Xie et al. (2017) used the Baidu Searching Index to investigate the association of online investor sentiment with asset returns and found a co-integration relationship between online investor sentiment and asset returns. The sentiment impact was weak in predicting the securities prices, asset returns, and asset volatilities. There was no effect of structural break points of online investor sentiment on asset pricing movements.

2.6 Investor Sentiment and Market Returns in Bull and Bear Market States

Baker and Wurgler (2006) studied the impact of high and low levels of investor sentiment on various types of equity returns and observed a negative relationship during low sentiment periods and a positive relationship during high sentiment periods in the case of all the six selected stocks under study. By using daily data from five capital markets of developed countries, Dhaoui (2015) studied the impact of rational expectations and behavioral biases on the variability of trading and found that behavioral biases have a significant effect on trading, whereas rationality has no significant effect. Cheema et al. (2020b) found that investor sentiment is a reliable momentum predictor for subsequent monthly market returns in China, as an increase (decrease) in sentiment moved toward higher (lower) future returns. However, they concluded that the positive relationship between investor sentiment and subsequent market returns was only significant during the boom and bust period characterized by high or low sentiment followed by high or low market returns. Thus, they found that the predictability of investor sentiment was limited to the bubble period, and outside of that period, it failed to reliably predict market returns in China. This implied that the association between investor sentiment and market returns depended on market conditions, and the results from the bubble period could not be generalized to other periods. Smales (2014) used VIX as a proxy tool to gauge investor sentiment and observed its strong effect on asset prices, leading to inefficient asset allocations. This sentiment affected the returns across firm value, size, telecom industry, technological industry, and small-cap stocks being most responsive to sentiment. Sentiment had a greater influence on market returns during recessions and stocks susceptible to speculative demand. Emmanuel and Ahmed (2020) investigated the impact of 5 individual investor sentiment predictors on Nigerian equity market returns using multiple regression techniques and found a positive link between shifts in sentiment predictors and Nigerian equity market returns for some of the selected variables; however, the arbitrage conditions intensified the influence. The study also revealed that bullish sentiment led to higher market excess returns, but bearish sentiment led to lower excess returns. Li and Yang (2017) found that individual stock sentiment not only affected the stock prices of cross sections but also revealed diverse effects during different market states and exerted the greatest effect on the stock of small-sized firms during market downturn states. Kadilli (2015) was the first to examine the predictability of financial stock returns within a panel regime-switching framework. By using the Two Panel Regime-Switching Model, he investigated the predictive effect of investor sentiment on annual stock returns of financial companies in developed countries and found an insignificantly negative effect during normal times and a significantly positive effect during crises times, but the predictive ability was less evident for short-term returns. Chuang et al. (2014) investigated the asymmetric predictive effect of investor sentiment on equity market returns during an economic recession and expansion regimes and found a significant predictive effect for market returns during the economic expansion regimes but not during the recession regime. This implied that sentiment performed better in predicting returns of portfolios based on various characteristics during an economic expansion, supporting the implications of behavioral theories.

Ho and Hung (2012) observed indirect relationship between consumer confidence and market returns in three of the four countries. Investor sentiment was able to forecast equity returns for up to one year during bearish market spans (Feldman and Liu, 2017) however, with varying intensities across the markets Corredor Casado et al. (2013) having stronger impact in developing countries (Corredor Casado et al., 2015). This varying impact was attributed to stock characteristics and was considered primarily a global phenomenon. The study also suggested that sentiment is transmitted through behavioral mechanisms, making local regulatory actions less effective in limiting the effect of asset bubbles.

Westheide (2009) conducted an event study to analyze the impact of already published investor sentiment indices just after their publication on Germany and US market returns over intermediate time horizons. They found that publicized investor sentiment indices significantly affected returns, but the signs remained unaltered till intermediate time horizons. Further, using a survey-based investor sentiment index, they concluded that investor sentiment predicted the return in both countries' understudy, but investor sentiment failed to continue its predictability after 1994 in the US market. Ho and Hung (2012) used the consumer confidence index to assess market returns of developed countries and the European Commission economic sentiment index to assess market returns of European countries and observed that consumer confidence proved a good predictor for market returns in France, Italy, and US only. In contrast, European Commission's economic sentiment index did not predict the equity returns in Europe. A shift in consumer confidence impacted conditional volatility in all countries except Australia and New Zealand; however, the European index only showed its impact in the UK and France.

In a study carried out by Shi et al. (2022) in 6 emerging markets by selecting 10 industries over fourteen years, it was observed that the relationship between local investor sentiment and expected industrial returns was significant, but global investor sentiment showed insignificant results. Schmeling (2009) analyzed the effect of consumer confidence on expected equity returns across 18 industrialized countries and found that high sentiment levels were associated with lower future stock returns. The negative relationship held true for various types of stocks and forecasting horizons. Furthermore, the sentiment's effect on returns was more prominent in countries with lower market integrity and a higher tendency towards herd-like behavior and overreaction. In Asian emerging markets, Anusakumar et al. (2017) found that stock-specific sentiment had a positive relation with returns, whereas market-based investor sentiment had a negative relation with returns. Vuong and Suzuki (2020) analyzed the link of investor sentiment with equity returns in Australia, Hong Kong, and Japan using two sentiment indicators-Volatility Index (VIX) and Consumer Confidence Index (CCI) and revealed a significant impact of sentiment on concurrent returns, with VIX having a stronger influence than CCI. However, the predictability for future returns based on sentiment was not determined.

Daszyńska-Żygadło et al. (2014) investigated the way equity returns of eight emerging markets (Turkey, Brazil, South Africa, India, Poland, Mexico, Russia, and the Republic of China) were influenced by investor sentiment and investor optimism indexes and found a positive relationship between excess equity returns and investor sentiment in Brazil whereas in China positive relation was observed between excess equity returns and investor optimism. Moreover, the relationship was more sensitive during negative sentiment and optimism indexes in Mexico, Brazil, India, and China. Gu and Xie (2019) constructed an index to reflect investor sentiment and built a model considering sentiment and the intensity of trade conflicts to examine the impact of trade conflicts on the equity markets of the US and China through a behavioral finance perspective and showed an asymmetric effect of Chinese and US investor sentiment on market performance and negative impacts of trade conflicts on both markets and their major industries. The study predicted future stock prices and returns, with worse performance observed in markets with higher trade conflict intensity. Zi-Long et al. (2021) constructed the 'International Investor Sentiment Composite Index' by taking transaction data from China, Hong Kong, and the US market to study international investor sentiment toward market returns. In the Chinese market, the proposed index appeared a significant predictor for future returns. They also observed that negative sentiment was a more powerful predictor of returns than positive sentiment. An asymmetric tail correlation was observed between the sentiment-return relationship. Further, international investor sentiment served as an alarm of extreme market conditions. Horta and Lobão (2018) employed both global and extreme dependence structures using copula models and statistical tests to investigate the relation of investor sentiment with equity returns in seven European markets and found its dependency at lower extremes and independency at upper extremes. These findings indicated that financial stability improved while considering the impact of regulatory decisions on investor sentiment and supported short-selling bans during market turmoil. The study emphasized the importance of considering investor sentiment for regulating and better understanding financial market behavior.

Al-Jabouri and Oleiwi (2020) investigated the influence of investors' emotions on returns in the Saudi and Iraqi Stock Exchanges, using financial variables for three sectors in each market and indicated that the impact of investor sentiment varied across markets and sectors, with negative sentiment were dominant in the Iraqi market and positive sentiment were dominant in the Saudi market. The Saudi market was more susceptible to risk than the Iraqi market. The Markov Regime Switching Model was used to investigate the impact of US investor sentiment shocks on returns of emerging frontier Asian (EFA) markets and found that US sentiment, bullish, and bearish market shocks were the main contributors in inducing variation in EFA stock market returns. Thailand was the most sensitive market to global sentiment shocks. Relying merely on the spillover effect from developed to emerging and frontier equity markets looked inappropriate (Rehman et al., 2020). Zhang et al. (2021) used VAR- TVP model to investigate the effect of investor sentiment in one country on the return of another country, selected dual-listed companies of the US and China, and observed that investor sentiment had a significantly positive correlation with the relative price differences. Moreover, the contagion effect and linkage in both countries' equity markets were observed. Limongi Concetto and Ravazzolo (2019) studied the impact of investor sentiment on returns of the US and EU equity markets and found that sentiment indexes had a strong predictive power for equity returns in the US market but weak for the European market. Additionally, the study found a spillover effect from the US to Europe when trying to predict European stock market returns with US sentiment indices and vice versa.

2.7 Social Media-based Measures of Investor Sentiment and Market Returns

Da et al. (2015) constructed a new measure of investor sentiment called the "Financial and Economic Attitudes Revealed by Search" index by considering the volume of households' internet searches, and it was found that this measure was able to predict short-term return reversals and temporary increases in both mutual fund flows as well as volatilities. Lachana and Schröder (2022) compared the effectiveness of various media sources in the determination of the behavior of investors and found social media more promising than traditional media. Among the three indices constructed by Xu et al. (2021), both social media-based and internet news-based investor sentiment indices proved best in predicting equity returns, whereas traditional newspaper-based indexes appeared insignificant predictors. Furthermore, the social media-based sentiment index proved the best predictor during expansionary periods, while the internet news-based sentiment index proved the best predictor during recession periods. More accurate predictions were obtained when both indices were used collectively in a model. Fang et al. (2021) constructed an investor's sentiment index by taking into account "dictionary-based linguistic text" and "web-based news messages" through Fintech approaches and found that (a) optimistic and pessimistic investor sentiment had respectively significant positive and negative effects on contemporaneous equity returns that were reversed soon, (b) negative impact of pessimistic investor sentiment was more profound than the positive impact of optimistic investor sentiment, (c) volatility of market returns was increased by optimistic investors and decreased by pessimistic investors, and (d) increase in market volatility, created by the high level of optimism, remained more persistent for longer times than that of the normal level of optimism. Zeng (2020) were the pioneer in developing an individual investor sentiment index termed "GubaSenti" by conducting a textual analysis of the sentiment dictionary called "GubaLex" that was based on equity posts taken from Online financial forums of the Chinese market. This index was more flexible in measuring individual investor sentiment regarding the aggregate market, industrial, sectoral, and individual stocks at various frequencies. This index proved better than Baker and Wurgler's measures in predicting market behaviors in the short run. Farina and Palma (2019) through analysis of 960,808 posts of Economics Blogs over 5 years, constructed two "Economics Blogs Sentiment Divergence" (EBSD) indices to investigate the impact of the divergent opinion of investors on the efficiency of equity markets and found a negative relation between the two.

The role of mass media information was also found important in influencing investors' decisions. Lee et al. (2002) analyzed messages posted on Stock Twits related to Apple incorporations using a linear regression model and found a positive relationship between investor sentiment and equity returns of Apple corporation. McGurk et al. (2020) conducted a textual analysis of social media posts and determined investor sentiment as a factor in abnormal stock returns. Coqueret (2020) noted that when stocks of firms were studied individually, news-based sentiment did not act as a good predictor of returns; instead, aggregate stock returns were better used to predict investor sentiment. The magnitude of predictability for returns depended upon the model used in the study. They acknowledged the refinements made in proxies used to measure investor sentiment but also felt the need for further improvements. Taking internet search volume data from Google trends, Beer et al. (2013b) created an investor sentiment index for the French mutual fund market and found that current returns of mutual funds were affected by investor sentiment. Furthermore, these funds were predicted by sentiment but in a reversal pattern in the short term. Xue and Comite (2020) conducted a systematic review of the literature on news sentiment and its relevance to equity returns and found the ability of news to influence investor sentiment and trading behavior. However, the relationship between news sentiment and excess returns was insignificant due to the influence of other factors such as interest rates, emergencies, and economic conditions. Rehman (2021) emphasized the significance of investor sentiment in the Pakistani stock market through news, social media, and market-based indicators at the firm and aggregate levels.

2.8 Linearities and Symmetries in the Nature of Equity Returns and Investor Sentiment Link

Investor sentiment was found able to predict the equity returns under different market regimes (Chuang et al., 2010), and during expansion regimes (Chuang et al., 2014). Uygur and Tas (2012) found a negative relationship between the higher level of investor sentiment and index returns of three countries, which was attributed to the price pressure effect of noise traders. Chen et al. (2014) showed good predictive power of investor sentiment for stock movements in the market. Huang et al. (2015) took into account the 6 proxies already used by Baker & Wurgler and applied Partial Least Square (PLS) method to construct a new index termed as "aligned investor sentiment index" and used it to analyze its predictability for portfolio and aggregate market returns and found significant results. They claimed that this index was able to predict cross-sectional returns also. Dalika and Seetharam (2015) constructed a composite investor sentiment index by combining the four linear indirect measures to explore the predictive effect of composite investor sentiment on the South African equity market and found that sentiment had a rich and broader impact on securities of the South African markets. Furthermore, a significantly negative effect of highly volatile, small, extreme, and growth stocks with returns was found more prone to the sentiment of optimists and speculators while less prone to sentiments of arbitrageurs during spans of high sentiment. This effect was reversed during spans of low sentiment. Neves et al. (2016) applied the Autoregressive Vectors Model by using the least squares method to analyze the linear impact of the Consumer Confidence Index (CCI) on Portuguese market returns under different market regimes and observed that pessimistic investors induced linear behavior, and the relationship was more evident during recession times. Bujang et al. (2015) applied linear a regression model to explore the predictive effect of fundamental factors and sentiment index towards future equity returns and showed a strong negative relationship between fundamental factors and future equity returns while a weak negative relation between sentiment index and expected equity returns. Okey et al. (2017) applied OLS regression and Granger Causality techniques to investigate the relationship between investor sentiment and expected returns in the equity market of Nigeria and found a significant positive dynamic effect on Nigerian stock market returns. Change in investor sentiment had a unidirectional causality toward equity market returns.

Mbanga et al. (2019) found that investor sentiment was influenced by attention, but attention was not the influence of sentiment. Attention also mediated between sentiment and aggregate equity returns; this relationship was stronger when the investors were more inattentive. Moreover, the nature of the relationship was observed as linear between sentiment and returns. Rapp (2019) utilized linear techniques on a sample of German small-cap stocks to explore the effect of earning announcements on the relationship between the predictive effect of moods and sentiment of investors and excess returns in short-term and indicated that moods were positive indicators in predicting short-term equity returns, negative moods had significant negative influence whereas sentiment has no effect. Chen et al. (2022) applied multiple linear regression models on data from 9 industries and investigated the impact of bullish investor sentiment on equity returns and found significant positive results for all selected industries. Cheng et al. (2019) collected data about comments of investors about the market from Social Network Sites (SNS) by utilizing crawler technology and used text processing technology to decompose the collected data into words, and then, from these words, created a databank termed "financial sentiment lexicon" and used this databank to develop an investor sentiment index for markets of China. Furthermore, they applied linear regression analysis on this created index to test the predictability regarding equity returns and observed that it was able to predict the returns, and it was further proved that the comments of investors were useful for creating an investor sentiment index. Maksim and Iuliia (2021) studied the influence of the level of news tone sentiment on equity prices of 49 Russian public companies and found a positive relationship, which was linear and without a declining marginal utility effect. Bannigidadmath (2018) analyzed the predictive ability of consumer sentiment for aggregate market returns and monthly returns of 9 Indonesian industries in linear terms. It was found that it predicted positively and significantly in 3 out of the 9 industrial sectors; however, the magnitude was different across the sectors; a few sectors were predicted during an expansionary period, while others were predicted during recession periods. Aggregate market returns were not predicted by changes in consumer sentiment, and no reversal effect was observed in sectors.

2.9 Non-linearities and Asymmetries in the Nature of Investor Sentiment and Market Returns Link

The inability of linear regression models to find relationship of multiple independent and dependent variables on equity returns, (S.Chitradevi, 2016) paved path to use nonlinear regression models for this purpose (Tuyon et al., 2016) and it was found that in both bearish and bullish market spans the results were different. Investor sentiment was proved as predictor of equity returns (Dergiades, 2012; Balcilar et al., 2018; Xie, 2017) even in bearish as well as bearish market conditions Huang et al. (2015), but at the same time (Bekiros et al., 2016; Cagli et al., 2020) proved its inability in the prediction of returns. Easaw and Ghoshray (2008) identified the symmetric behavior in the case of UK household sentiment and asymmetric behavior in the case of the US household sentiment market. An increase in a shift in sentiment was observed rapidly as compared to a decrease in swings in sentiment. Sentiment expansion and contraction and cyclical economic nature were also observed differences in the US and UK. Yang et al. (2013), using a principal component analysis, established an investor sentiment index and applied GARCH-M models to evaluate the impact of the movement of the sentiment of investors on returns of diverse portfolios and observed asymmetric effects toward different portfolios.

Goh et al. (2018) augmented Fama and French three-factor model with market-wide based investor sentiment and applied Markov Regime Switching Framework to examine the nonlinear effects of market-wide based investor sentiment on asset prices in Bursa, Malaysia and found a nonlinear two regimes switching pattern. The results also showed that a shift in investor sentiment had significant predictive power in switching the regimes dynamics between the Malaysian bull and bear market. During bear markets, the positive sentiment of investors had a greater transition probability of regime switching. Furthermore, the market premium fell when the stock market switched from bull to bear markets, whereas value and size premiums increased. Ma et al. (2018) employed Quantile Regression and found that investor sentiment predicted the aggregate equity returns at lower quantiles; however, it lost its forecasting power at upper quantiles. Furthermore, the ability to forecast returns gradually increased from the lowest to the highest. Wang et al. (2018) constructed investor sentiment indices and applied the nonlinear and linear Granger Causality Test to find the relation of investor sentiment with returns under bullish and bearish market conditions and found a one-way linear causality and two-way non-linear causality between sentiment and return relationship; however, this observed nonlinear causality was inconsistent under the bullish and bearish market states. Jiang et al. (2019) used a multi-scale and linear/nonlinear integrated Granger causality method in the US economy to investigate the causal relation of decomposed time series of investor sentiment on equity returns at various time terms and found a strong nonlinear and linear causal association only between long-term investor sentiment and equity returns. Lao et al. (2018) employed the Baker and Wurgler (2006) index and the wavelet method to investigate the impact of the term structure of investor sentiment on equity returns in nonlinear and linear settings for the US economy. Investor sentiment was observed to have a long-term bilateral Granger Causality effect on equity returns in both nonlinear and linear settings.

Dong (2020) utilized Noise-Based Abnormal Institutional Investor Attention (NBAIA) to find its relation with abnormal stock returns and found U shaped relationship between the two: stocks associated with more negative (positive) sentiments generated much lower (higher) abnormal returns; however, such movements were temporary. In Australian equity markets at the time of economic policy uncertainty, the high beta stocks led toward low profits at lower quantiles, and this negative behavior of returns disappeared with the revival of high investor sentiment. This relationship also strengthened during low sentiment periods (Nartea et al., 2020). Al-Nasseri et al. (2021) combined the textual sorting of 289024 online tweet posts from 'Stock Twits' and extracted the investor sentiment index for the DJIA stocks, and applied the Quantile Regression technique to explore the contemporaneous and predictive effect of investor sentiment on the dispersion of equity returns and found both effects heterogeneous throughout the distribution of returns. At upper quantiles, sentiment had a positive association with contemporaneous equity returns, and at lower quantiles, it showed a strong negative predictive effect for future equity returns.

2.10 Optimistic and Pessimistic States of Investor Sentiment and Market Returns

Lemmon and Portniaguina (2006), using the consumer confidence index, measured investor optimism and found that investor optimism did not predict market momentum and value premiums. Contrary to it, Bolaman and Evrim (2014) proved that consumer confidence could serve as an alternative proxy for measuring investor sentiment. Liu (2015) observed a positive relationship between bullish investor sentiment and trading volume. Zhang and Yang (2009) used OLS and GATCH-M techniques to explore the influence of negative and positive investor sentiments on the formation of asset prices and observed a significant link; however, the magnitude of positive investor sentiment was higher than negative investor sentiment. Zhang and Yang (2009) created a comprehensive sentiment index and tested its relationship with equity returns through regression analysis and showed that positive sentiment changes had a greater impact than passive changes, and the sentiment was acknowledged as a systematic factor in equity price formation, contributing to systematic risk. Lee et al. (2002) proposed that high sentiment/optimism strengthened the momentum effect due to the slower diffusion of bad news and continued overreaction to positive signals. It was observed that momentum profits occurred during optimistic spans only, whereas the formation of hedge portfolios experienced long-run reversals, suggesting that biases of investors contribute to short-run momentum and long-run reversals. The relation of investor sentiment with future equity returns was observed in 12 developed countries, and it was found that sentiment negatively predicted aggregate equity market returns on average across countries. The predictive power of sentiment varied across countries and was influenced by cultural and institutional factors. The effect was more pronounced for mid and large-cap stocks, small-growth stocks, and mid and large-value stocks and countries with high scores on uncertainty avoidance, masculinity, and long-term orientation and low on individualism and indulgence. Institutional quality alleviated the effects of noise trading, while culture was a constant factor influencing the sentiment-return relation (Sinke, 2012). Zakamulin (2016) carried out an event study of the VIX index to measure the behavior of equity markets and observed abnormal gains around peaks in the VIX index, and this abnormality in returns was attributed to an overreaction of investors toward bad news and further proved that VIX index could be used to measure investor sentiment. Using daily data from five years in the Indian stock market, Aggarwal (2017) examined the impact of the volatility sentiment index and investor's mood sentiment index on current equity returns and observed that changes in sentiments had a statistically significant and more explanatory relationship with market returns. The investor mood (optimistic investor sentiment) had a positive relation, whereas the VIX index (fear guard index) had a negative relation with equity returns. Dhaoui and Khraief (2014) proved a significant relationship between pessimistic investor sentiment and changes in the trends of French financial markets. The impact of pessimism was more vigor than that of optimism, whereas being an indirect indicator, the agent-based sentiment was comparatively smooth. (Chu, 2017) utilized the regime-switching approach in exploring different patterns of mispricing during bearish and bullish sentiment periods and proved that mispricing was higher during bullish sentiment periods than bearish sentiment periods. Li and Yang (2017) constructed a composite individual investor sentiment index based on Principle Component Analysis, by using panel data to explore the effect of individual sentiment on equity share prices and found that individual sentiment proved as a strong factor in deviating the equity prices and this effect was more prominent during bearish market trends. However, stocks of small firms showed more price fluctuations than those of larger stocks. Shams (2018) studied 83 companies listed on the Egyptian stock exchange market to examine the relationship of investor sentiment with equity prices and observed a significant positive relationship between the two. The investor optimism affected the premiums of MAX stocks negatively, and this negative effect remained persistent in subsequent months of the high sentiment period in China (Cheema et al., 2018). Kräussl and Mirgorodskaya (2017) used media pessimism as a proxy of investor sentiment to forecast financial market returns and volatility over a long period and found that media pessimism had forecasting power for negative returns from 14 to 17 months and positive returns from 24 to 25 months and positive volatility from 1 to 20 months. They also claimed media pessimism is a better predictor than the index of Baker and Wurgler (2006). Affuso and Lahtinen (2019) captured Twitter sentiment from Twitter posts and used it as a direct measure of investor sentiment to analyze its impact on daily equity returns and found a significant effect of both positive and negative sentiments on returns. It further showed that the effect of negative Twitter sentiment was more pronounced than positive Twitter sentiments. According to Chue et al. (2019), individual stock returns and aggregate market returns showed more synchronization during high sentiment periods. Shang et al. (2022) studied transaction aggressiveness of the retailers, dealers, foreign institutional investors, and mutual fund flows in the Taiwanese equity market during different market sentiment periods and observed a positive relationship between the number of transactions and market risk for retailers and a negative relationship between the two for foreign institutions and mutual fund. When the market sentiment was fearful, all types of selected investors showed higher transactions; however, mutual fund flows reflected a lower amount of transactions during panic market periods. The equity prices were found to be directly and indirectly influenced by the imbalances in orders for all four types of investors. Niu et al. (2021) used wavelet phase angle, and wavelet coherence approaches in the Chinese market and observed a strong relationship between investor sentiment and industrial equity returns during normal periods and significant positive during crisis periods. Cepni et al. (2021) used a panel Vector Auto-Regression on monthly data to examine the effect of unconventional and conventional monetary policy shocks on the stock markets of eight advanced economies at various states of investor sentiment. It was found that the response towards equity prices under expansionary.

2.11 Extremely Optimistic and Extremely Pessimistic Investor Sentiment and Market Returns

Rousseau et al. (2008) found that divergent confidence levels had a divergent impact on trading volume. Further, moderate levels of underconfident and irrational traders outperformed as compared to rational traders, resulting in better earnings for irrational traders than rational ones. Fung et al. (2010) extended the overreaction study to Asian international markets and found that intraday price reversals existed in future markets after extreme movement in the U.S. market. Further, they observed a magnitude effect; overreactions were more prominent in the latter than in the initial periods, and the overreactions were greatly reduced after calm-down periods. Sheu et al. (2009) tested causal relationships between sentiment and returns in different market scenarios using a threshold model to detect extreme sentiment levels and found that sentiment measures exhibited a feedback relationship with returns. The dichotomization of sentiment into extremely higher and extremely lower levels proved as leading indicators. It was discovered that the bullish/bearish ARMS performed as a leading indicator in a more bearish market, while derivative market sentiment performed as a leading indicator in a more bullish market, which confirmed the noise trader explanation of sentiment-based driven market behavior. Liu et al. (2011) through, direct and indirect processes provided insight into the extreme sentiment indicators (ESIs) that had leading impacts on the financial markets of Taiwan. Extreme Sentiment Indicator constructed by extracting the values of trading volumes that were above or below one standard deviation from the mean; the values above one standard deviation were considered as Extreme Bright Sentiment Indicator (EBSI), whereas the values less than one standard deviation were considered as Extreme Dark Sentiment Indicator (EDSI) to explore the heterogeneous role of extreme sentiments on Taiwan's market returns. The results demonstrated that Extreme Dark Sentiment Indicator (EDSI) had a significant negative relationship with spot and future market returns and in all markets dominated by the "price pressure effect," whereas Extreme Bright Sentiment Indicator (EBSI) had a significant positive relation with spot markets and negative for future market and dominated by price-pressure (a hold-more) effect in the future (spot) market. In short, extreme investor sentiment significantly affected market returns, but the magnitude depended on various factors.

Wu et al. (2016) applied a Panel Smooth Transition Regression framework and reconstructed the Fama-French three-factor model to explore the nonlinear and heterogeneous effect of investor sentiment on the risk premiums of corporations listed with the Taiwan Security Exchange and demonstrated that extreme optimism or extreme pessimism decreased the market premiums. These premiums were dominated by holding growth stocks than holding value stocks under extreme sentiment regimes. Furthermore, an increase in the volatility index (investor sentiment) decreased the size premium, and value stocks earned more returns than growth stocks under normal sentiment regimes. Based on the specifications of the Panel Switching Transition Model, Namouri et al. (2018) proposed a non-linear panel data model to capture the effect of investor sentiment regimes on equity return to facilitate the investor sentiment to act time varyingly, non-linearly and asymmetrically depending on the investors' risk appetite and market states and empirically tested it. For empirical analysis, they decomposed investors' sentiment into three regimes: neutral, optimistic, and overly optimistic. In the first regime, the results were insignificant because of the presence of rational investors who held the market without sentimental investors. In the second regime, the results were significant and positive because the presence of irrational investors held the market through their optimistic and overconfident behavior. In the third regime, the results were significant and negative because of the presence of extremely overconfident investors whose sentiments dominated the market; however, this dominance was corrected subsequently after a certain threshold. Moreover, the magnitude of investor sentiment on returns varied considerably at each regime. Li et al. (2019) constructed a sentiment indicator to examine the behavioral heterogeneity of interacting investors and found this sentiment indicator a contributor to several financial anomalies such as fat tails and volatility clustering of returns. Su et al. (2020) studied the effect of investor sentiment on Chinese equity markets using quantile regression analysis and observed the remarkable effect of investor sentiment on gold, foreign exchange, and bond markets of public sectors but not on the bond market of companies. These markets were more durable during extreme sentiment periods.

Langnan (2020) examined the Chinese stock market and found that stocks with larger unrealized gains and losses had higher returns in the following month due to investors' trading behavior. Stocks with greater unrealized gains had more impact on future returns than those with larger unrealized losses. The asymmetric V-shaped disposition effect existed in Chinese investors and was stronger than the traditional disposition effect. This effect was significant for more speculative stocks due to the anchoring effect of investors, thus generating asymmetries. During optimistic sentiment periods, the effect of Loss Overhang on future stock returns did not remain significant. Dahmene et al. (2020) revealed that extreme optimism/extreme pessimism smoothly switched the market from bullish to bearish/bearish to bullish states, depending on the heterogeneous responses of the market participants and the investors' risk appetite. Dahmene et al. (2021) explored the non-linear impact of monetary shocks, changes in investor sentiment, and risk aversion on equity market returns in developed countries by applying the Smooth Transition Model (STR) and observed a negative relationship between a high level of risk aversion and index returns during a positive shock of volatility index. In some markets, a negative relationship was also observed between restricted monetary policy and returns during low regimes, and this effect was more prominent for high liquidity and high regime markets. Furthermore, extremely optimistic and pessimistic investors in the market changed the market regime from bearish to bullish. Fariska et al. (2021) constructed a microblogging individual investors' sentiment index based on Twitter and classified the sentiments into positive, negative, and neutral by applying text mining algorithms. They applied Vector Auto Regression and Impulse Response techniques to analyze the effect of constructed indicators on short- and long-term returns during the pandemic of COVID-19 in Indonesia. A causal relationship between microblogging investor sentiment and equity returns was observed. Du et al. (2022) proved the existence of concept momentum in the Chinese stock market, where ambiguous concept-oriented information created slow information diffusion leading to abnormal returns. A concept-momentum strategy of buying past winning concept stocks and selling past losing concept stocks generated pronounced abnormal returns beyond the explanation of risk factors, firm-level momentum, or industry-level momentum. Slow information diffusion through the under-reaction and cross-stock lead-lag effect channels drove concept momentum, which was stronger for relatively ambiguous concepts, less investor attention, and high-sentiment periods.

2.12 Persistent Deviation in the Nature of the Relationship between Investor Sentiment and Intrinsic Value

Barberis (1998) claimed that earning behavior of firms remained moving between any two regimes. At the first regime, earnings had mean-reverting behavior because of corrections in the mispricing behavior, and at the second, earnings had trending behavior, indicating continued earnings after an increase at an initial stage. Ling et al. (2010) used Vector Auto Regressive models to investigate the relationship between sentiment and short- and long-horizon returns in public and private commercial real estate markets and found that sentiment could push asset prices away from their fundamental values in both markets but the effect was more persistent in private markets due to limits to arbitrage and delayed in price revelation.

In contrast, public markets experienced quick price reversals following periods of sentiment-induced mispricing. Kadilli (2014) applied Regime Switching Model with smooth and threshold transition to analyze the predictive power of business cycle indicators, investor sentiment, and financial variables for equity returns using panel data of financial markets of developed countries. A strong predictive power of business cycle indicators for long-term returns was observed but not for the short term.

Inflation and investor sentiment were strong predictors of returns during the crisis period. The regime Switching Model proved a better model than linear models. Kholdy et al. (2014) used the Vector Auto Regression approach to examine the relative dynamic effect of institutional and individual sentiments on the US stock returns over long-term bullish periods up to ten years and compared it with shorter bust and boom cycles and indicated that individual investors' sentiments had an effect on the returns during prolonged upward trends in stock prices whereas institutional investors' sentiments had an influence on returns only during high volatile periods. Stambaugh et al. (2014) observed the role of investor sentiment on equity returns' anomalies and found that high sentiment led to higher long-short anomalistic profits, and the crux was that there was consistency across these anomalies. Under-reaction to good news in the stock market was a driver of weekly momentum returns.

A study conducted in Asia Pacific, Europe, the United States, and Japan considering a dataset of 10.1 million news items discovered that stocks with significant and positive news exhibited stronger return continuation and exhibited a similar pattern of under-reactions toward good news in the selected international markets (Huynh and Smith, 2017). Zhu et al. (2019) observed a significant positive and more persistent relationship between stocks with an increasing (decreasing) trend with (positive) negative abnormal returns. Yang (2021) applied the ARMA-GARCH model to explore the magnitude and effect of northbound capital (as a proxy for investor sentiment) on Shanghai Composite Index returns and found significant results between Northbound and Shanghai market rates of return, but the reversal effect was not observed.

Saxena and Chakraborty (2022) used the Google Search Volume Index for capturing investor attention and, applied the Panel Least Square method to explore the effect of investor sentiment on the relationship between investor's attention and the returns of the firms listed on the National Stock Exchange of India. They demonstrated that an increase in abnormal attention had a significant effect on an increase in abnormal returns, and this effect became strengthened for firms following positive sentiments.

2.13 Individual and Institutional Investors and Market Returns

Gric et al. (2021) claimed that the sentiment of individual and institutional investors had different effects in predicting returns and that the negative effect of sentiment was insignificantly increased with time. Further, the nature of returns was unimportant; the sentiment effect was more substantial in the US compared to Europe, and the frequency of data and selection of model and methodology influenced the results. Da et al. (2015) found that high Aggregated Retail Attention to individual stock was strong and contrarian predictor for future returns, especially during high investor sentiment periods. This predictability was robust and lasted for up to four weeks. They did not find the same predictability with 'market factors', 'direct retail attention,' and 'aggregated institutional attention.' The results suggested that the combination of high retail attention to individual stocks and high investor sentiment led to market-wide overvaluation. Gao et al. (2021) discovered that institutional investor sentiment had greater predictive power in forecasting equity market returns than individual investor sentiment. They also concluded that sentiments of institutional traders reflected future cash flow news about firms, which in turn impacted future price expectations, leading to better market efficiency and price discovery.

2.14 Rational and Irrational Traders and Market Returns

Verma et al. (2008) found that sentiments of rational investors had a stronger impact on stock returns of the S&P 500 and Dow Jones Industrial indexes than sentiments of irrational investors. While market returns initially responded positively to irrational sentiments, they were corrected with negative responses to rational sentiments. Victoravich (2010) investigated the difference between sophisticated and unsophisticated investors and their affective reactions to earnings regarding a firm and found that unsophisticated investors were more prone to news of positive earnings than sophisticated ones. Chuang et al. (2014) selected U.S. and domestic market gains to study the trading behavior of Asian individual and institutional investors. They observed an increase in their trading during bullish market periods and that this effect was more prominent during the optimistic period of investor sentiment, extremely high return market periods, and when the market was facing short-sale constraints. Chau et al. (2016) observed that sentiment traders in the U.S. stock market relied on survey-based indicators and reacted asymmetrically to shifts in sentiment by trading more aggressively during low sentiment periods. Further, the sentiment traders were more sensitive to buying and selling during bear market conditions and tended to base their trades on individual surveys rather than institutional surveys. Ryu et al. (2017) examined the role of trading behavior and investor sentiment on Korean market asset returns and found that higher Korean stock market returns were induced by high investor sentiment. Furthermore, individual (institutional) trades were negatively (positively) associated with Korean market returns, signifying the information inferiority (superiority) of individual (institutional) investors. Chu (2017) pointed out that the sentiment index of Baker and Wurgler was dependent mainly on fundamental information (more than 60%); therefore, to remove this weakness, he used a novel approach to obtain a new sentiment index, and he named this index “purged sentiment (IS-P) index .”The IS-P index better captured the sentimental effect for cross-sectional stock returns and performed better than the index of B.W. and other survey-based sentiment indices used then. Bayram (2017) investigated the dynamic impact of irrational and rational 'consumer' and 'business' sentiments on 100 index returns of Turkey and observed that rational sentiments of both had a significant positive effect on the index returns. Li et al. (2017) studied the herding differences between individual and institutional investors using trading volume and concluded that institutional investors had better information; they relied more on private information and reacted asymmetrically to bullish and bearish market movements. However, individual investors had less information; they relied more on public information, were more sensitive to attention-grabbing events and market sentiment, and did not react asymmetrically to up-and-down movements in the market. Regardless of these differences, it was observed that in herding, institutional and individual investors paid close attention to trading with one another in forming a consensus.

Tran et al. (2020) developed an agent-based model (ABM) of a stock market with three types of traders (noise, fundamental, and technical) and calibrated it using Bayesian optimization and showed that fundamental traders made up 9-11% of all traders in the Dow Jones Industrial Average index. The simulated data reproduced important features of real stock markets, such as leptokurtosis, heavy-tailed returns, and volatility clustering. Xue et al. (2020) investigated the relationship between investor sentiment and with 'innovative investments' of firms in China and explored the intermediary role of institutional investors. They observed that privately owned enterprises (POEs) and state-owned enterprises (SOEs) showed varied investment behaviors. SOEs had a negative effect on innovation investment, whereas institutional investors had a positive intermediary role in promoting innovation investment in POEs, no such role was observed for institutional investors in SOEs.

Pornpikul and Nettayanun (2022) used the stepwise and multiple linear regression models to examine the influence of investors' irrationality and rationality on the portfolio returns of the U.S. equity market. Both rational and irrational investors explained the value, momentum, and ETF portfolios; however, the explanatory powers of rational and irrational investors differed depending on the nature and time terms of portfolios. Moreover, the irrational influences remarkably increased their importance in explaining returns during a financial crisis. Aziz and Ansari (2021) investigated the impact of Google search volume on stock prices of Indian firms and found that with an increase in search volume, equity returns, liquidity, and volatility were increased. This increase was for a short time and was reversed in the subsequent week. The association between Google searches and future excess stock returns was also affected by market sentiments. Kim and Lee (2022) constructed an investor sentiment index using daily data from the 'relative strength index,' 'turnover rate' and 'buy-sell imbalance' to examine the relations of investor sentiment in two different Korean stock markets named KOSPI and KOSDAQ and introduced the mobile trading and examined its effect on the sentiment-return relationship. The results of the study were: (a) Korean stock markets returns were significantly affected by the investor sentiment index, (b) KOSDAQ returns were more affected by investor sentiment due to high individual participation, (c) mobile trading transformed the irrational investors into informed, rational investors and, (d) firm characteristics also affected the sentiment and return relationship.

Positive feedback and negative feedback strategies were used by individual investors and institutional investors respectively during trading and their sentiment proved significant predictor of returns (Kim et al., 2020), the effect was more sensitive during spans of high volatility and lower margin requirements (Gao and Xie, 2020). Negative and short term swing in investor sentiment proved better in predicting the return than that of positive and long term swings (Lv et al., 2022).

Fisher and Statman (2000) found that: (a) the predictive effects of sentiment for the cross-sectional future stock returns were conditional on the state regimes, (b) long-short portfolios formed on book-to-market ratio, earning size, and dividends had strong predictive patterns that were conditional on the state as well as sentiment regimes and (3) the value premiums and size were also associated with state and sentiment regimes. Predictability of the investor sentiment for returns was measured by using the index of Baker & Wurgler, and it was observed that animal spirit shocks had a significant impact on shifts in investor sentiment and stock returns. Investor sentiment was observed as a noisy representation of autonomous animal spirits, partially responsible for the apparent predictability of returns based on investor sentiment (Sohn, 2013). Karakatsani and Salmon (2008) analyzed the non-linear connection between investor sentiment and market returns using the S&P-500 index and supported two non-linear hypotheses. The study revealed that institutional sentiment significantly affected monthly returns, while individual sentiment did not. Aggregate idiosyncratic volatility was observed to have a positive impact on subsequent returns and institutional sentiment. This was the indication of sentiment risk compensation. The importance of considering regime shifts when forecasting returns was also highlighted. Kadilli (2014) evidenced the predictability of investor sentiment for financial returns conditioned with an economic state that meant greater predictive power for financial returns during financial and economic distress in developed countries. Beer et al. (2013a) combined direct and indirect sentiment measures to develop a composite sentiment measure, which proved a better predictor of returns than other sentiment measures. Dash and Mahakud (2013) constructed an investor sentiment index by using implicit sentiment proxies and found that it had a negative effect on equity returns in the Indian stock market. This negative effect was due to overvaluation caused by positive sentiment, resulting in lower expected returns in the subsequent period, and the cross-sectional return variation was attributable to the sentimental effect.

Huang et al. (2014) constructed an investor sentiment index and examined its forecast ability for the aggregate as well as individual stock market returns. The selection of companies was based on value, momentum, and size. It was found that this aligned index had much greater predictive power than existing sentiment indices and macroeconomic variables. The predictability was both economically and statistically significant. An index was developed by Huang et al. (2015) to measure investor sentiment and was claimed that the new index was capable of excluding noise components and performed better in predicting asset returns than indices already in use and macroeconomic variables. Fang et al. (2015) found that when high-frequency sentiment signals were used to predict returns over the short and medium terms, the relationship between these two was negative or reversed. However, when low-frequency sentiment signals were used, the relationship was stronger and in the direction of the future returns using Dynamic Factor Modeling and Ensemble Empirical Mode Decomposition. Sibley et al. (2016) decomposed Baker and Wurgler (2006, 2007) investor sentiment index into two components named 'explanatory' and 'residual' and tested their predictive effect on returns. Its predictive power for stock returns was influenced by the business cycle state and risk state, whereas the residual component was of minimal significance for predicting returns. Chu et al. (2015) claimed that many non-fundamental predictors lost their predictive power during low sentiment periods, and their predictive power was significant only during high sentiment periods. In their framework, 20% (80%) times were classified as a high (low) sentiment period, and at this state, fundamental predictors seemed more prevalent than non-fundamental predictors in forecasting equity premiums.

Habibah et al. (2017) compared the Volatility Index (VIX) and Google Search Volume Index (GSVI) in explaining the S&P 500 index returns and found VIX as a more strong predictor of stock market returns as compared to the GSVI index. In addition, VIX had a more prominent effect on its past values in the Vector Auto-Regression model and the Autoregressive Distributed Lag (ARDL) and nonlinear ARDL models. French (2017) took dealer account, local, foreign, and institutional investor groups and used their daily net purchases as leading indicators for sentiment and applied the VAR framework to examine the impact of selected 4 groups' sentiment indices on the Stock Exchange of Thailand (SET). Of the four groups, the SET returns were influenced only by the local individual group of investors, whereas the foreign investor group had the least significant effect on market returns.

Demir (2017) specified three factors (investor sentiment, stock classification, and market regimes) to explain their effect on excess stock returns and used Markov Process to determine two market regimes. They observed that all three factors strongly determined the excess market returns. Xu and Zhou (2018) demonstrated that a weekly aligned sentiment index constructed using the Partial Least Squares method could predict characteristic-sorted portfolio returns in the A-share market of China. Short-term changes in investor sentiment positively affected future stock returns, having the strongest impact on the small-size portfolio. Pönkä (2018) explored the relationship and directionality of sentiment of businesses, investors, and consumers with excess stock market returns in the US. It was found that measures of investor sentiment were useful and most commonly used predictors for stock returns. Whereas, measures of business and consumer sentiment showed varied predictive abilities for returns. Rizkiana et al. (2019) developed a composite sentiment index based on principal component analysis of investor sentiment measures from social media, google search volume, and news media sentiment and found positive correlations between each investor sentiment proxy and the composite index; however, sentiment measures alone did not predict stock returns.

Limongi Concetto and Ravazzolo (2019) used direct (surveys) and indirect investor sentiment measures of Baker & Wurgler and also of Huang et al to investigate the predictive effect of sentiment indices for market returns of the EU and US. They found these indexes had negative predictability for future stock market returns. The index of Baker & Wurgler appeared better in predicting US returns but weak in predicting European markets. Using the same indices, Cheema et al. (2020b) applied the Two State Predictive Regression model and observed that both indices had negative predictability for aggregate returns during spans of bullish sentiment at all-time terms. Tripathi and Dixit (2020) provided evidence that weekly, and daily returns at upper (lower) quantiles exhibited negative (positive) serial correlation across different markets. Gao and Xie (2020) found that institutional investor sentiment served as both economically and statistically significant predictors for the aggregate stock market. Gric et al. (2021) derived from the review of 30 investigations that when investors' sentiment was improved, the equity returns were significantly and negatively affected. It was also concluded that positively biased publications show the positive side of the results. Moreover, individual investors had a stronger predictive effect of sentiment on future returns than large institutional investors, and the effect was more pronounced in the US stock market compared to Europe. Leite and Armada (2017) developed a European Investor Sentiment Index using five proxies, tested its ability to predict returns using a dynamic factor and TGARCH model, and found it a strong and accurate predictor for returns in European and US markets. Habibah et al. (2021) incorporated investor sentiment as an additional factor with Fama & French five-factor model and, by applying the VAR and Granger causality tests, analyzed the effect of sentiment on five-factor premia and vice versa. It was concluded that investor sentiment encompasses some information to explain the Fama-French five-factor premia, especially investment premium, size premium, and profitability premium. Size premium and market risk premium were increased during low sentiment spans (a negative relationship), whereas investment premium, profitability premium, and value premium were increased during high sentiment spans.

Gakhar and Kundlia (2021) used lexicon-based sentiment analysis and developed a regression-based predictive model for examining the impact of Twitter sentiments on movements of equity markets using four directional, positive, negative, and negative sentiment scores total. It was found that positive Twitter sentiments predicted stock returns and volatility better than liquidity. Wang (2021) used the MIDAS model to construct mixed frequency individual stock sentiment index and investigated its predictive power for future excess returns. It was found that the variations of excess stock returns were well explained through the higher frequency of individual stock sentiment. Mixed high-frequency sentiment exerted greater influence on excess returns, had a stronger explanatory power for the variation of excess returns, and forecasted the returns better when a higher frequency of individual stock sentiment was used. Ma et al. (2021) conducted a study in the Chinese stock market and found that the difference between short and long-term moving averages of trading volume (MAVD) negatively predicted stock returns even after controlling other factors. The MAVD effect was more potent and more pronounced for stocks with high investor attention, volatility, and arbitrage limits. This was due to individual speculative trading behavior. This effect was weakened over time, indicating market overreaction and gradual correction.

2.15 Measurement of Investor Sentiment Index

Measurement of investor sentiment had been a focus of research because it was considered a qualitative behavioral factor. Therefore, quantifying the behaviors of investors about the market had been challenging. Previous studies employed several different methods to measure investor sentiment. Several studies employed the survey to collect data on the behavior of investors. Some studies employed media reports, publicly available documents, events, etc. Survey data was thought to capture the short-term effects only (Fisher and Statman, 2000). Therefore, predictability in the short run was much disputed among researchers. Some studies employed market-centered indicators such as trading activities and price movements for setting up the investor sentiment index. Some researchers used a single proxy for investor sentiment. For example, Mushinada and Veluri (2018) employed trading volume only as the proxy for investor sentiment. Haritha and Rishad (2020) documented that a single proxy is not enough to explain investor sentiment because there were a number of factors that caused variations. While a single sentiment proxy that characterized investor sentiment was a simple way to quantify investor sentiment, a few researchers expressed doubt about its validity and credibility (Brown and Cliff, 2004);(Brown and Cliff, 2005). There was no guarantee that a single sentiment measure included all the relevant information regarding feelings. Currently, a variety of proxies for market sentiment are statistically complete and easily available. Baker and Wurgler (2006) used six sentiment proxies that are not useable today in totality, e.g. IPOs had been banned several times in China's stock market. So, Li (2020) did not include the number of IPOs and average first-day returns. They also used some sentiment proxies, such as the psychological line index, new stock accounts, and new fund accounts, which accurately represented the sentiment level in China's stock market.

2.16 Investor Sentiment and Short Horizons Prediction of Market Returns

A number of studies are available that prove investor sentiment is an important factor in predicting stock returns at least in the short run, but it loses its predictive ability in the long run because over-valued stocks revert to their intrinsic value after one month. Yumei and Mingzhao (2009) employed the Vector Autoregressive model and examined the impact of investor sentiment on near-term equity returns and found it a predictor for near-term equity returns. In the German market, Lux (2012) used weekly survey data to develop an instrument called "opinion formation" and used it as a tool to measure investor sentiment and its effect on returns over short and medium horizons. He observed a gradual decrease in the impact of sentiment on returns moving from short to medium term. Significant results were found in the short-term and long-term relationships of the investor sentiment index with future market returns of the National Stock Exchange and Bombay Stock Exchange indices using the Error Correction Method and Johansen Co-Integration test (Dash and Mahakud, 2013).

Sun et al. (2016) combined data from social media, internet news, and news wires sources and applied textual analysis to construct the 'Proprietary Dataset Based High-Frequency Investor Sentiment Index' to explore its predictive power for equity market returns. Evidence showed that lagged half-hour investor sentiment predicted the intraday S&P 500 index returns and this predictability persisted for at least 2 hours, and similar results were observed for bond and equity Exchange Traded Funds. Mehrani et al. (2016) used Arms Adjusted Index and Vector Auto Regression analysis to analyze relationships among sentiment states, equity return, abnormal gains, and volatility. They observed losses in short-term portfolio returns under both optimistic and pessimistic states of investor sentiment. Combining the normal market sentiment with behavioral finance strategies increased the performance, whereas contrarian strategies gave more significant results than momentum strategies. Klemola et al. (2016) collected the volume data from Google Search to gauge the shift in negative and positive attention of investors in the market and used this information to analyze the predictive ability of optimistic and pessimistic investor sentiment for near-term equity returns. It was observed that a shift in positive search volume termed a "market rally," and a negative shift in search volume, termed a "bearish market" or "crashed market," had forecasting ability for near-term equity returns. Herceg (2017) investigated the predictive ability of investor sentiment on different U.S. sectors using four sentiment measures and observed that sectors with younger and high-growth companies were more influenced by investor sentiment, especially over 3 and 10-month forecast horizons. Yelamanchili et al. (2019) used the Index of Consumer Sentiment in the Indian stock market and found that it had a negative forecast ability for short-term returns of 'small-cap,' 'mid cap' and 'BSE-500 index' but not for 'large cap' stocks. The study also revealed the presence of noise trading and investors' over-reaction in small-cap stocks and no volatility clustering or persistence except in the case of small-cap stocks. A negative impact of consumer sentiment on small-cap stocks was not persistent for longer terms.

Exploiting the Bull-Bear index in the Chinese market, Zhaohui (2005) proved that the psychology of investors could predict future returns and suggested an appropriate time term for prediction as 1-month or 1-quarter. Chang et al. (2022) analyzed stock message board posts and found that sentiment expressed in messages could predict returns of small stocks for one to two days. Local posts exhibited greater predictive power than nonlocal posts, which showed more trend-chasing sentiment. There was no evidence of long-term predictive power.

Ling et al. (2010) investigated the relationship of investor sentiment with real estate market returns in private and public sectors over the short and long term and found a positive correlation between sentiment and quarterly returns in both sectors in the short term. However, the public sector experienced a reversal effect in the long term while the private sector exhibited a momentum effect.

Huang et al. (2014) applied Principle Component Analysis to find the investor sentiment' impact on returns of specific industries and found a significantly positive correlation between sentiment and current period returns and a negative correlation with one lag period. Furthermore, investor sentiment was classified into optimistic and pessimistic states; optimistic sentiment positively affected most industries, while pessimistic sentiment had no effect. The study also used a Two-State Markov Regime switching model and showed that the effect of sentiment on industrial returns varied depending on the market state. In a study, trading data of 87373 French investors were collected for over 8 years and analyzed by Roger 1 (2014) to create an investor sentiment index. This sentiment index was used to predict portfolio returns and negative relation of investor sentiment with subsequent monthly returns of the portfolios was observed. Hu et al. (2013) analyzed the sentimental effect of irrational and rational investors on asset returns of the Chinese market over the short and long horizons. A significant and stable relationship was observed between the predictability of irrational investors and asset returns in the short run, whereas it was reversed in the long run.

Moreover, rational investors also had predictive power to accurately forecast short- and long-term returns. Johnson and Naka (2014) used a long-horizon asymmetric response regression format to analyze the forecast ability of consumer sentiment for equity returns in the long and short run under different age groups and found asymmetric results: equity returns were more influenced by a negative shift in investor sentiment than a positive shift in investor sentiment. However, younger investors were found to be less risk averted than aged investors.

Tuyon et al. (2016) investigated the predictive power of Stock Futures, Business Conditions, and Consumer Sentiment indices for equity returns over short and long horizons in the Malaysian market. They found that all indices predicted the equity returns significantly, and the results were asymmetric regarding time. Investor sentiment had a positive effect on returns in the short term and negative in the long term in Taiwan equity market Chang et al. (2017), and a strong relationship over short and long horizons in Indian equity market (Dash and Maitra, 2018).

Ding et al. (2004) proposed and tested a new model with multiple risky assets by extending the noise trader model of De Long et al. (1990) to explore the predictive relation of market-wide investor sentiment index with contemporaneous and subsequent cross-sectional equity returns over the short and long horizons. A higher positive relation was observed between short-term market-wide sentiment and contemporaneous equity returns. There existed a negative relationship between long-term market-wide sentiment and subsequent equity returns. Seok et al. (2019) found that in the short term (2 to 3 trading days), higher overnight equity returns were followed by higher equity returns, whereas in the long term, higher overnight equity returns lowered stock returns in the Korean market. Ruan et al. (2020) created a new investor-sentiment indicator (ISI) index by employing a deep learning approach to analyze its impact on future equity returns over the short and long horizons and found it the best predictor in forecasting the returns. A positive relationship was observed between future monthly returns and negative with long-term future returns. Chue et al. (2019) evidenced that equity prices were affected by aggregated investor sentiment index and found that the effect was more prominent for those stocks whose returns were highly synchronized at that time. Mascio and Fabozzi (2019) used Logistic Regression Analysis on each of the 5 selected models to examine the predictability of investor sentiment for S&P 500 index equity returns for up to 1 month and found that in 4 out of 5 selected models, 'investor sentiment' proved as the best predictor in predicting returns. Kaivanto and Zhang (2019) used eight investor sentiment indicators at specific time horizons ranging from 1 to

48 months to predict equity returns and found that three non-composite indicators had consistent predictive power. From the three well-performing indicators, they derived a new investor sentiment index named "targeted composite index" that performed better than the index of Baker & Wurgler for forecasting the returns.

Ruan et al. (2020) used a deep learning approach to develop an investor-sentiment indicator (ISI) for forecasting stock market returns. ISI was found to have a positive correlation with monthly returns but a negative association with subsequent returns over longer periods. Monthly ISI was positively linked to dividend growth rate, indicating investors' expectations of future cash flows influenced return predictability. Janková (2020) analyzed the intensity and correlation between investor sentiment and equity returns over the short and long run using wavelet analysis and observed that the intensity of the relationship was strong at the initial level that gradually decreased. It was also observed that the relationship between stock index return and investor sentiment was strong during COVID-19. Vuong and Suzuki (2020) focused on six Asian Pacific markets. They created a market investor sentiment index by collecting data regarding Volatility premium, Consumer Confidence Index, and Advanced-Declined ratio to analyze its impact on future equity returns and found a significant short-term relationship between sentiment and expected returns.

Moreover, they decomposed the sentiment index into local and global sentiment and found local sentiment to be a driver of the global market. Kim and Ryu (2020) used predictive regression and investigated the ability of investor sentiment and macroeconomic factors to predict future equity returns over short and long horizons. He observed that the sentiment of investors predicted the equity return for up to 1 month but did not after 2 months; however, the Term Spread variable predicted the return negatively irrespective of the time. Further, investor sentiment was proved to be a better predictor of returns than macroeconomic factors. Banchit et al. (2020) applied predictive regression analysis to analyze the predictability of the Trading Volume and Consumer Confidence Index for short and long-term portfolio returns in the stock markets of Australia and New Zealand. They observed that these sentiment metrics' possessed strong and positive forecast ability for short-term portfolio returns, whereas weak predictability for long-term portfolio returns.

He (2022) collected data from the leading financial newspapers of the Chinese market and measured the 'textual tone' aggregated from these newspapers by employing dictionary-based and 'Word2Vec' techniques to construct textual and media-based investor sentiment indexes. They analyzed its effect on Chinese returns of publicly listed A-share firms over short and long horizons. A significant positive effect of media-based investor sentiment on returns was observed in the short run, while a significant negative effect was observed over the long run.

2.17 Investor Sentiment and Long Horizon Prediction of Market Returns

Trent (2005) found a significant negative relationship for future returns from 2 to 3 years. Chang et al. (2009) utilized the Error Correction Granger Causality model and Co-integration test in the Borsa Istanbul stock market to capture the long-term impact of the Consumer Confidence Index (investor sentiment) on monthly returns and found the results significant. Kandır et al. (2015) utilized the Error Correction Granger Causality model and Co-integration test in the Borsa Istanbul stock market to capture the long-term impact of the Consumer Confidence Index (investor sentiment) on monthly returns and found the results significant. Shi et al. (2022) studied a broad set of online posts regarding investors' opinions on the largest Chinese equity forum. They applied text mining methods with two-step sentiment classification, text representation, feature extraction, and data cleaning to create an individual investor sentiment index. This index was applied to explore the prediction effect on CSI 300 equity returns and found the results significant.

Furthermore, a positive prediction effect on returns in the short term was observed, which was reversed over the medium term. An asymmetric effect between the high level of investor sentiment and equity returns was also observed. studied a broad set of online posts regarding investors' opinions on the Chinese largest equity forum and applied text mining methods with two-step sentiment classification, text representation, feature extraction, and data cleaning to create an individual investor sentiment index. Liston-Perez et al. (2018) utilized predictive regressions and Multivariate GARCH models to analyze the dynamic relation of investor sentiment with equity returns across various portfolios and forecast horizons and found that high levels of investor sentiment led to lower future stock returns over the next 1-24 months and that this current sentiment influence on equity returns decreased as the forecast horizon increased. The study also found positive and significant correlations between investor sentiment and small-cap and market portfolios, with varying levels of influence over time. Finally, excessive mispricing was found to be due to noise trading, particularly in small-cap and value stocks. Khan et al. (2020) collected weekly Google trend data to construct an investor sentiment index for the U.S. household's industrial sectors. They applied Frequency Domain and Wavelet Granger causality approaches to analyze the causality effect and the predictive relation of households' investor sentiment index with industrial returns over the short and medium terms. A strong predictive relation and causal effect of investor sentiment with U.S. equity returns were observed for both short and medium terms.

2.18 Investor Sentiment and Volatility

Yeh and Lee (2000) utilized the GARCH model to investigate the information transmission process and the response of investors to unexpected returns in the stock markets and observed that the impact of unpredicted negative returns (bad news) on future volatility was greater than the impact of unanticipated positive return (good news) of the same magnitude in Taiwan and Hong Kong, but it was fully reversed for Shenzhen and Shanghai markets. Lee et al. (2002) examined the impact of the Investor Intelligence Sentiment Index (noise trader risk) on conditional volatility by applying the GARCH-M model. The results revealed that sentiment created a systematic risk that increased prices. Shifts in sentiment had a contemporaneous positive association with excess returns. Bearish investor sentiment increased the volatility and decreased the returns, whereas bullish investor sentiment decreased the volatility and increased the returns. Li and Zhang (2008) examined the link between individual investor sentiment and volatility in China using newly opened stock trading accounts and found that shifts in sentiment had a negative relationship with the equity market's volatility. Further, a decrease (increase) in volatility was observed when the investor turned bullish (bearish). Beaumont et al. (2008) measured the Individual investor sentiment index by using aggregating inflows and outflows of U.S. domestic-oriented mutual funds and used the GARCH-M specification to investigate its effect on returns and conditional volatility of three main market indices of the U.S. The observed results revealed that the influence of individual investor sentiment on conditional volatility was significant and asymmetric. This impact was increased during the bearish sentiment periods.

Lin (2009) found that the relationship between future stock returns and volatility depended on sentiment at the beginning of the month. Small-size stocks, growth stocks, and stocks with low dividends were affected by sentiment, while mid-term winners and short-term losers experienced lower returns during high sentiment periods. On the other hand, long-term losers earned positive returns. The study also showed that certain stocks were not necessarily less volatile despite being easy to arbitrage and attracting rational speculation. Chuang et al. (2010) investigated the relationship of investor sentiment (Trading Volume) with conditional volatility in the Taiwan stock market by employing the 'Generalized Autoregressive Conditional Heteroscedasticity in Mean (GARCH-M)' model and found that it had a significant negative effect on conditional volatility of returns of Taiwan stock market. Foucault et al. (2011) observed a positive relationship between retail trading activity (noise traders) with the volatility of stock returns using the French stock market.

Liston and Huerta (2012) analyzed the relationship of investor sentiment with the volatility of the Mexican stock market returns by using the GARCH-in-Mean model and found that positive sentiment changes insignificantly decreased the conditional volatility in the subsequent periods. However, negative changes in sentiment increased the volatility. The study highlighted the important role of investor sentiment in generating volatility in the Latin American market. Chi et al. (2012) used mutual fund flow for different stocks, examined its relation with volatility in the Chinese stock market, and observed significant results. Zou and Sun (2012) studied the heterogeneous role of investor sentiment on volatility during bullish and bearish market states. It was observed that above-average misperceptions of heterogeneous noise traders pushed asset prices to deviate from their fundamental value, which in turn engaged the optimistic investors in more trading that resulted in further deviations in the asset prices with ultimate excess returns for the optimistic investors. Conversely, the returns of pessimistic investors less increased their risk level.

Ho and Hung (2012) examined the effect of investor sentiment on the market volatility in the 3 Asia-Pacific and 4 largest European and U.S. countries and found that when investor sentiment was changed, it significantly influenced the conditional volatility in most selected countries. Rahman et al. (2013) applied the GARCH-in-Mean model to investigate the effect of noise traders on the volatility in the Bangladesh equity market and evidenced that changes in the magnitude of bearish and bullish investor sentiment indirectly affected returns through an asymmetric effect of volatility.

Kumari and Mahakud (2015) combined 10 aggregate market-related sentiment proxies to construct an aggregate sentiment index for Indian stock markets and employed VAR-GARCH models to explore the role of sentiment index in the dispersion of market returns in the creation of volatility. Investor sentiment had a significant effect on volatility. Past investor sentiment and past returns affected the volatility positively and negatively. They also found that pessimistic investor sentiment influenced the stock market volatility and made the markets highly volatile. Sayim and Rahman (2015) utilized generalized Impulse Response Functions (IRFs) generated from Vector Auto Regression (VAR) and investigated the influence of unexpected movements in the Consumer Confidence Index on stock returns and volatility in Turkey. Unpredicted changes in the irrational and rational Consumer Confidence Index had a significant positive impact on returns, whereas an unanticipated increase in the rational component had a significant negative effect on market volatility. Uygur and Taş (2014) used weekly indices of nine countries and, by applying the EGARCH model, determined that the conditional volatility asymmetrically influenced earning shocks during bullish sentiment.

Papapostolou et al. (2016) proved that investor sentiment is important in studying the mean-variance relationship to gain utility and that the predictive effect of investor sentiment is powerful when negative forecasts are considered. Suresh and

George (2016) constructed a composite irrational market sentiment index using monthly data to explore its impact on return volatility in India's Bombay Stock Exchange equity market. Based on ARDL modeling, the results showed a significant long-term relationship between irrational investor sentiments and return volatility. Yacob et al. (2016) applied Factor Analysis on 5 suggested proxies and constructed a composite investor sentiment index in the Malaysian stock market to examine the capability of this index in predicting the excess volatility of the Malaysian Kuala Lumpur Composite Index (KLCI). They found that this index was reliable in predicting volatility. Labidi and Yaakoubi (2016) observed a negative relation between aggregate volatility risk and stock returns during low sentiment periods using time series and cross-sectional analysis. However, this relationship lost its importance during high sentiment periods. Frugier (2016) investigated the link between investor sentiment with volatility and expected returns. It was found that investor sentiment increased the returns but decreased the volatility, and this relation was conditioned by the management of portfolios. Naik and Padhi (2016) used Principal Component Analysis, constructed an investor sentiment index using seven market-related implicit indicators, and applied various models to explore its relationship with stock return volatility in the Indian National Stock Exchange. They found a significant symmetric negative relationship between conditional volatility and overall investor sentiment, which became asymmetric when sentiment was decomposed into optimistic and pessimistic components. Sadaqat and Butt (2016), using a top-down approach, created a broadband investor sentiment index in the Pakistan equity market to analyze the effect of this index on conditional volatility. Optimistic investor sentiment increased and pessimistic investor sentiment decreased the volatility and the effect of investor sentiment on conditional volatility was also different across sectors. The negative relationship between returns and volatility was contrary to the prevailing concept wherein a positive relationship existed between returns and volatility.

Aydogan (2017) used a country-specific consumer confidence index and applied the TGARCH model to analyze its effects on volatility and to capture the asymmetric effect of positive and negative news in nine stock markets. A statistically significant and negative effect for Germany and France, whereas a statistically significant and positive only for Ireland, was observed. Stock market volatility was more sensitive to negative shocks in investor sentiment except in Ireland. This sensitivity was due to the presence of the leverage effect. An asymmetric effect was also observed for all markets. Maitra and Dash (2017) carried out the time-frequency domain analysis by applying a wavelet approach to examining the sentiment and volatility relationship in the Indian stock market and found a weak conditional correlation between the two. Investor sentiment affected the realized and conditional volatility over short and medium horizons. Small stocks were more prone to sentiment impact, and significant movements were noted during different volatile periods at different frequencies.

Ahmed (2018) utilized the ARCH model to examine the impact of various proxies of investor sentiments on stock market volatilities in Pakistan. A significant positive relationship was observed between Dividend premiums, Margin Funds Flows, and Stock Market Turnover Ratio with volatility. An insignificant relation of Stock Traded Volume, average first-day returns on IPO, closed-end Funds discounts, and Margin Borrowings with volatility was also observed. Escobari and Jafarinejad (2019) used conditional volatility of investor sentiment to construct a method to model investor uncertainty by taking data from six major US stock indices and found that during economic depressions and periods of low sentiment, investor uncertainty increased. Investor sentiment and returns had a positive relationship, attributed to the positive link between investor uncertainty and market risk. Zhang et al. (2018) used 'Web Crawling Technology' to creep investors' comments relevant to Fujian Expressway and SANY stock and then used a semi-supervised machine learning method to construct an investor sentiment index. Data regarding the trading volume and daily closing stock prices were collected through Qianlong software and applied Granger Test Method and VAR model to explore the relationship between constructed investor sentiment index and stock market volatility. The results demonstrated that negative emotions and returns had a one-way Granger causality, whereas returns and trading volume had a two-way Granger causality. Furthermore, with variance decomposition and the impulse response function, trading volume significantly affected returns, and negative investor sentiment showed a significant negative effect on both returns and volatility.

Rupande et al. (2019) used a set of proxies and constructed an 'investor sentiment composite index' and, by applying 'Generalized Autoregressive Conditional Heteroscedasticity' models, found that this index significantly affected the volatility of returns in the Johannesburg Stock Exchange market. Siddiqui and Roy (2019) applied Quantile Regression Model to analyze the asymmetric impact of returns on changes in volatility by considering the investor Volatility Index (VIX). The negative relationship between contemporaneous returns and volatilities was observed and this relationship was conditioned by investor sentiment. This contemporaneous negative relationship between volatility and returns was attributed to the presence of risk-averse investors and their heterogeneous beliefs.

Griffith et al. (2020) utilized propriety investor sentiment measures developed by Thompson Reuters Market Psych by taking data from a commercial-strength comprehensive textual analysis to explore the interaction between media content-based investor sentiment, market returns, and volatility. They selected 4 measures (gloom, fear, stress, and joy) of investor sentiment from their index, which reflected both optimism and pessimism of small investors, and applied Threshold Generalized Autoregressive Conditional Heteroscedasticity models to find the reliability of these sentiment measures to predict market returns, and also to examine the effects of these sentiment measures on market return and volatility. The results revealed that stress (sentiment measure) had a small effect on the market return, and joy and gloom did not have a predictive effect on market returns. Fear had a long-lasting effect on market returns and conditional volatility. Haritha and Rishad (2020) applied Principal Component Analysis to construct an irrational sentiment index using monthly data on market-related implicit indices and modeled it in the Granger causality and GARCH framework to explore its role in determining stock market volatility. It was observed that irrational investor sentiment significantly affected market volatility. The asymmetrical facets in an inefficient market contributed to excess market returns and volatilities. Zeng (2020) employed the BEKK and DCC GARCH models to investigate the dynamic spillover effect and linkage of various investor sentiment indicators with Chinese stock market returns volatility using monthly returns. The results demonstrated that most of the sentiment indicators (volume of transactions last month (TURN), consumer confidence index (CCI), new investor account openings last month (NIA)) had significant linkage with the CSI 300 index of return fluctuations and volatility spillovers whereas, several indicators of investor sentiment did not fully explain the effect on CSI 300 index. Chakraborty and Subramaniam (2020) captured investor sentiment by utilizing a survey-based measure termed as 'Consumer Sentiment Index' and a market-based measure termed as 'Market Mood Index' and applied Quantile Causality Regression to examine the cross-sectional and asymmetric effect of these measures on returns volatility in India. A shift in negative investor sentiment dropped the volatility, whereas a positive relationship existed only when a relationship existed between volatility and returns and also in the formation process of investor sentiment. He et al. (2020) analyzed the nonlinear impact of investor sentiment on volatility in the Chinese stock market and found that pessimistic investor sentiment had a nonlinear effect on stock market volatility subject to a balanced market.

Gakhar and Kundlia (2021) examined the impact of Twitter sentiments on the movements of the equity market using four sentiment scores and found that negative sentiment scores were better predictors of liquidity and volatility in the equity market. Nogueira Reis and Pinho (2021) used 5 sentiment proxies to construct an index for evaluating investor sentiment for European and U.S. markets and applied dynamic and TGARCH models to test its impact on volatility. It significantly affected variances in the returns of Europe and U.S. markets. It was also observed that investor sentiment had an asymmetric effect on volatility during moderate, strong troughs, and peaks of sentiment periods.

Aziz and Ansari (2021) observed that with an increase in Google search volume, the volatility of stocks of Indian firms increased. However, this increase was short-lived and reversed in the following week. Hu and Sun (2021) constructed an investor sentiment index using Principle Component analysis to analyze its impact on the volatility of equity markets and found that shocks to stock market returns impacted stock market volatility.

Sharma and Chaturvedi (2021) used GARCH, EGARCH, and Bivariate VAR models in 9 sectors of Indian stock markets and found that investor sentiment and return volatilities had a significant relationship between them. Reis and Pinho (2020) constructed an "Individual Investor Sentiment Index" index by involving

5 individual sentiment proxies and applying a dynamic factor model. Then they applied the TGARCH model to predict returns and volatility in European and U.S. markets. This index well predicted market returns and volatility and was a valid and vital measure for predicting and monitoring stock market behaviors in Europe. Abdelmalek (2022) used Quantile Regression to analyze the association between the VIX volatility index and expected realized volatility for developed markets at different frequencies of time. It was found that VIX had predictive power for future volatility at higher and lower frequencies and that the relationship was not symmetric across all quantiles.

Naik (2022) used GARCH-M and E-GARCH-M models to investigate the relations of investor sentiment with Indian stock market return volatility and found the relationship significant. Jiang et al. (2021) developed a Spatial-Temporal Dynamic Panel model by considering the spatial interaction of stocks and examined the dynamic role of investor sentiment on volatility by using data from Shanghai A-share stocks. A positive relation between investor sentiment, spatial spillover, and cumulative temporal effects on volatility was observed. The cumulative temporal effect was more sensitive to geographic and economic factors.

Song et al. (2023) constructed a new sentiment indicator by applying Scaled Principal Component Analysis to predict equity market volatility in China and proved it a powerful predictor in predicting the volatility in the Chinese market. More importantly, predictive power of this predictor was tested before and after financial crises (the Chinese stock market turbulence and sub-prime mortgage crisis) and the spread of the pandemic (COVID-19) and found its predictability significant. Muzindutsi et al. (2023) utilized MS-VAR, GARCH, GJR-GARCH, and E-GARCH, models and assessed the response of conditional volatility to investor sentiment under different market conditions. Investor sentiment showed a significant effect on the risk premium and an increase in positive changes in investor sentiment decreased conditional volatility.

Pillada and Rangasamy (2023) constructed a sector-specific investor sentiment index by using principal component analysis, market data, and implicit indices and applied the DCC-GARCH model to analyze the relationship between these. To assess the directionality of the relationship, the Diebold-Yilmaz technique was employed, and investigated the volatility of returns in India during the pandemic. The presence of an asymmetric impact of sentiment was found that led to an increase in extreme volatility. The study confirmed a bi-directional relationship between investor sentiment and asset returns. Anese et al. (2023) investigated different methods to extract investor sentiment proxies and explored the influence of publicly released financial news on the S&P 500 index. For the classification of investor sentiment, automatic labeling techniques, dictionaries, and leverages advancements in natural language processing were employed and for the classification problem, short and long-term memory neural networks were utilized. It was observed that investor sentiment showed a significant impact on the market within a 20-minute time span after the release of the news and sentiment derived from dictionaries yielded more meaningful results as compared to sentiment based on equity index returns.

The study also suggested that the mapping process between financial returns and the news was not effective, highlighting the importance of utilizing alternative sentiment measures for accurate analysis. By taking into account the business cycle, Zanatto et al. (2023) investigated the impact of governance, environmental and social news on equity market volatility in Portugal and found that this news contributed a significant role in the reduction of volatility during non-crisis periods and the positive and negative news became significant in the period leading up to the financial crisis. Moreover, neither the content of ESG news nor volume affected volatility during economic downturns, suggesting that ESG concerns become less crucial during such periods. Rohilla et al. (2023) identified 22 variables as proxies for investor sentiment and employed principal component analysis to select the top 11 principal components as sentiment sub-indices in India and developed a pioneering analysis of the long-term relationship of investor sentiment equity. The volatility was measured by applying the GARCH model and then the ARDL model to examine the relationship between sentiment and equity market volatility. The results indicated that the majority of sentiment sub-indices had a significant and negative impact on Indian stock market volatility in the long run and it was inferred that bullish sentiment corresponded to negative volatility in the long term and vice versa.

2.19 Market Risk, Investor Sentiment, and Market Returns

The rational asset pricing models theorized a positive mean-variance relationship (Merton, 1973). Yu and Yuan (2011) investigated the influence of investor sentiment on the tradeoff of the market's mean and variance. A positive relationship between conditional volatility and expected returns was observed during spans of low sentiment but not during spans of high sentiment. It was observed that sentiment traders undermined otherwise positive mean-variance tradeoffs during high sentiment spans. It was also observed that returns had a stronger negative correlation with contemporaneous volatility during low sentiment periods. Ahmed et al. (2012) examined the role of investor sentiments on the tradeoff of mean and variance in the Pakistani market. They developed a composite index for investor sentiments, including KSE turnover, closed-end fund discount, and dividend premium. The study found that stock market returns were negatively related to variance during high-sentiment periods, while during low-sentiment periods, there was no significant relationship between returns and variance. Da et al. (2010) developed the FEARS index and found a strong relationship with the transitory component of daily volatility and that its correlation with VIX future returns was also reversed.

Ni et al. (2015) employed panel quantile regression to study the nonlinear predictive effect of investor sentiment on monthly equity returns in the Chinese A-share stock market over the short and long horizons and found this predictive effect significant from 1-24 months. This predictive effect was asymmetric and reversal: it was greater and positive in the short term for high stock returns and conversely small and negative in the long run. Aboura (2016) utilized an index prepared by the American Association of Individual Investors and applied Ordinary Regression and Quantile Regression to analyze the relationship of this index with the S&P 500 index returns. It was observed that when financial markets were bearish, the individual investor's sentiment index was found more informative. Gopal and Ramasamy (2017) used the Markov switching model coupled with a radial basis function network to predict prices, proposed a hybrid model to predict the one-day future price, and explored the risk of trading performance and investment decisions based on different values at risk (VaR) methods. Results indicated that for the selected stocks, the investment trading strategy and the investment risk provided better accuracy with the best investment decision. Piccoli et al. (2018) examined the impact of the consumer confidence index on the relationship between mean and variance in the Brazilian equity market and found that the relationship between conditional variance and raw stock returns was positive during low sentiment periods and negative during spans of high sentiment. Whereas small stocks had a negative relationship. The study suggested that the increase in less sophisticated investors during high sentiment periods led to a weaker risk-return relationship. Wang (2018) investigated the relationship between investor sentiment with mean and variance in 14 European equity markets and applied three approaches to defining investors' neutrality and determined bearish and bullish sentiment periods. The results revealed that the increased presence of individual investors and trading during bullish sentiment periods undermined the risk-return trade-off.

Du and Hu (2018) examined the factor premium of market-wide investor sentiment in the US equity market, in contrast to previous studies which focused on factor loading and hypothesized that the sentiment premium was negative if overpricing was more prevalent than underpricing and that it was particularly significant on days without macroeconomic announcements. The study was claimed to support these hypotheses, with important implications for capital budgeting, portfolio evaluation, investment, and risk analysis decisions. Shaikh (2018) examined the asymmetric effect of the Indian volatility index on stock market returns in Indian securities markets and observed an asymmetrically strongly negative relation between daily changes in the volatility index and stock returns. The magnitude of this asymmetrical effect was not identical. This relationship was more pronounced during peaked and more volatile sentiment periods for negative investors but not for positive investors. Zhang et al. (2019) proposed an investor sentiment index by combining specific factors and using principal component analysis and tested it statistically. A positive correlation between the sentiment index and the monthly rate of returns was observed. This index was also able to predict stock price trends and estimate a systematic risk using VaR and C-VaR models.

Chen et al. (2021) provided that hedge funds with higher exposure to macroeconomic risk did not earn higher returns as expected by the risk-return tradeoff. However, high macro-risk hedge funds generated higher returns following low-sentiment months, while the risk-return relationship was flat following high-sentiment months. These results suggested that standard asset pricing theory applies when market participants are rational, but sentiment-induced mispricing affects hedge funds with high macro-risk loadings. He et al. (2019) evidenced the association of higher current risk compensation with higher current return; there was a significant and negative correlation of returns with one lag period risk compensation. This negative correlation was due to the mean-reverting behavior of equity prices. Stock returns were positively correlated with current investor sentiment but not with the sentiment of one lag period. Negative sentiment was associated with risk aversion, while positive sentiment was associated with risk-seeking. Lin et al. (2019) proposed a Theoretical Equilibrium Asset and Options Pricing Model to predict excess market returns based on the 'skewness risk premium,' which measured the difference between physical and risk-neutral skewness. Empirical findings using S&P500 index options data showed that investors demanded higher risk compensation for holding stocks when the 'skewness risk premium' was high during periods of high-risk aversion, consistent with theory. However, in periods of low-risk aversion, the relationship weakened, and investors demanded lower-risk compensation. Keiber and Samyschew (2019) used Economic Sentiment Indicator developed by EU Commission and applied Conditional Multi-beta Pricing Model to investigate variation in risk premiums caused by changes in investor sentiment in European equity markets. A significant positive relationship between sentiment and contemporaneous excess returns was observed. In contrast, constructed sentiment risk premium was found to be negative, which was attributed to the unattractiveness of investors towards risk premiums while bearing sentiment risk in EA-11 countries over the examined period.

Escobari and Jafarinejad (2019) developed an index from the conditional volatility of investor sentiment index and tested it using US equity market data. They found that spans of bearish markets created more uncertainty that lowered investors' sentiment. Sentiment and returns were positively correlated due to the link between market risk and uncertainty. He et al. (2019) explored the effect of investor sentiment on the association between investor risk compensation and equity returns. Current IRC was found to have a sustainable positive effect on returns across all divergent states of sentiments, but it had no association with the contemporaneous magnitude of investor sentiments. However, past IRC negatively affected returns across different past sentiment signs but had no association with previous values of investor sentiment. Cagli et al. (2020) investigated the causal relation of the Consumer Confidence Index with equity returns of Borsa Istanbul (BIST) by employing the conventional Granger causality tests, and the time-varying recursive evolving window reached the conclusion that the conventional Granger causality test found a unidirectional Granger causality whereas, the recursive evolving window procedure not only detected Granger causality episodes but also detected a significant episode of Granger causality which accommodated the nonlinearities over the sample period.

Wang et al. (2020) investigated the impact of institutional investor sentiment on the relation of beta-return, and a positive relation during bearish periods and a negative relation during bullish periods were observed, indicating that institutional investors may also act as sentiment traders. Amiri et al. (2020) presumed the presence of noise traders who based their trading strategies on sentiment and examined its impact on the risk-return tradeoff in the US equity market. The sentiment of noise traders was measured using Baker and Wurgler indexes and Michigan Consumer Confidence. When tested using Merton's Intertemporal CAPM model, a significant and positive relationship between risk and returns was found. The use of GARCH in the Mean model resulted in a weak relationship. The study confirmed Merton's hypothesis that higher risk led to greater expected returns and contributed to the asset pricing literature from the behavioral finance perspective. The relation of analyst forecast dispersion with future market returns in the US was explored. The predictive power of aggregate dispersion for return existed before 2005, meaning the investor sentiment index could explain the dispersion effect but not after 2005. The weakening of the dispersion effect seen was not explained by 'put options' and 'institutional ownership' after the global financial crisis. The link between conditional equity premium and dispersion was a driving force for the dispersion-return relation. Stocks with short-sale constraints did not show a higher dispersion for returns in contrast to the overpricing theory (Liu et al., 2020b).

Hu and Sun (2021) observed that the association of the tail risk component with firm fundamentals and investor sentiment predicted the equity returns significantly and positively in the Chinese A-shares market. Li (2021) studied the predictability of Chinese Investor Sentiment using the nonparametric Causality-in-Quantiles test for volatilities and returns of 12 Asian Pacific equity markets. Empirical results showed a significant contagious effect from Chinese investor sentiment on Australian, Hong Kong, and Indian stock indices volatilities, whereas Chinese investors' sentiment had a very weak contagion effect on returns. He et al. (2022) applied Quantile Regressions to explore the moderating role of market-wide and individual investor sentiments on the relationship between risk and return in the US equity market. Across all quantiles, individual sentiment had a heterogeneous negative effect on risk and return tradeoffs. Individual sentiment also had an asymmetric effect; negative sentiment had a stronger impact than positive sentiment. It was more sensitive than market-wide sentiments, thus more important in finding prices and their variations.

Duxbury and Wang (2023) investigated the influence of institutional and retail investor sentiments on the relationship between return and risk in financial markets, while conventional finance theory suggested a positive correlation between return and risk, but empirical evidence had been inconsistent. The study considered the impact of both institutional and retail investor sentiments and found that the risk-return relation was distorted when this sentiment of investors grouped, rather than individual. Moreover, the study identified a cross-sectional pattern, indicating that the influence of investor sentiment on the risk-return relationship was more pronounced for some specified stocks. Morley (2023) utilized an EGARCH model to investigate the impact of 'Swiss/US exchange rate spanning' and the 'STOXX European market', indices on market returns and volatility and observed that subsequent referendums showed limited evidence with equity returns, however, a positive link with market returns and a negative link with market volatility was observed when considering pre and post-referendum of a three-day timeframe. A more comprehensive understanding of the effect on the economy was gained while studying the effects of referendums on risk and equity returns and it supported the idea that referendums reduce risks and increase economic returns. Liu et al. (2023) utilized 'Firm-Specific News Sentiment' and investigated its effect on the Chinese equity market liquidity and it was observed that firms that had an optimistic tone in their coverage of newscast experienced an increase in trading activities and reduced transaction costs and price effect. Moreover, a stronger predictive effect for equity returns by Pessimistic stocks was exhibited as compared to optimistic stocks. When liquidity was decomposed into components, a declined but significant liquidity premium was observed indicating that this sentiment contributed to the explanation of the liquidity premium. Kyriazis et al. (2023) utilizes 'market uncertainty' and 'innovative economic' measures derived from Twitter data to develop a Twitter-based investor sentiment and applied a non-linear Granger causality test to assess the influence of this sentiment measure on returns and volatility of the cryptocurrencies market. It was observed that Twitter-derived sentiment influenced the volatility, whereas uncertainty measures influenced non-linearly the examined cryptocurrency at both the upper and the lower quantiles. Extreme levels of investor sentiment had less affected the cryptocurrencies but were still profitable due to investor behavior being more aligned. Guo (2023) employed the GARCH model for the calculation of daily volatility and conducted Granger causality tests to examine the relationship of investor sentiment with volatility and equity-based returns and found that investor sentiment indeed affected the price volatility of China's stock market, and there was a reciprocal impact of investor sentiment with price volatility that gradually decreased. Furthermore, it was recommended that, for the enhancement of the functioning of the Chinese equity market, consideration of the perspectives of investors' sentiment is essential. Mugenda (2023) examined the predictability of the Kenyan equity market to accurately price securities, predict returns and the pricing effect of various factors (asset growth, market premium, value, profitability, and size), and employed a 'quantitative causal time series design' to explore how investor sentiment moderated the relationship between equity returns and risk premia in Kenya. Market and size showed a significant and positive coefficient, suggesting that investors demand higher returns for increased market-wide risk and exposure to small stocks, however, profitability showed a negative and significant coefficient, indicating that investors require lower returns for profitable investment strategies, investor sentiment showed moderating effect for asset growth, market premium, and value, sentiment showed no moderating effect on the relationship between equity returns and risk premia. Based on these findings, the study recommended an optimal model that incorporated market, profitability, size, and sentiment as proxies for systematic risk in investment decisions within the Kenyan market. Liu and Wen (2023) utilized Fama-Macbeth and panel regressions to investigate the relationship between intraday and overnight returns with market beta in the Chinese A-share market to find the reasons behind the weak correlation between full-day returns with systematic risk. Overnight risk premium in the Chinese A-share market was significantly negative, whereas the intraday risk premium was minimal when portfolios were sorted by factors such as stock characteristics, Book-to-Market ratios, and industry beta. It was also observed that the slope of the securities market line tended to approach zero due to the negative correlation between market risk and overnight returns and the combination of the uncertain intraday risk premium. Shen et al. (2023) utilized the 'Long Short-Term Memory deep learning' approach and developed a Chinese investor sentiment index to examine its impact on value at risk and returns during COVID-19. Investor sentiment showed a significant influence on equity returns and Value at Risk across both old and new energy sectors and a stronger impact was observed in the new energy sector. Furthermore, during COVID-19, the effects of investor sentiment intensified; with investors prioritizing risk considerations over potential returns. These results offered valuable insights for medium and small-sized investors in China, aiding them to optimize investment strategies and mitigate losses regarding extreme levels of risks.

2.20 Macroeconomic Factors and Market Returns

Humpe and Macmillan (2009) found that in the US market, the stock return had a positive and significant correlation with the industrial production index, a negative and significant correlation with the consumer price index and long-term interest rate, and an insignificant money supply. They observed similar results in the Japanese market, except that stock return had a negative and insignificant relationship with the money supply. This study suggested that the contrasting result in the US and Japan was due to the slump in the economy of Japan in 1990. Fong (2015) revealed that a model incorporating sentiment-related factors provided more accurate forecasts of market returns than the traditional macroeconomic variable model.

Shen et al. (2017) studied the pricing of macro-related factors on equity returns and found that assets exposed to higher risk gave lower returns. During spans of low sentiment, high-risk portfolios earned higher returns, and low-risk portfolios earned low returns. This relationship was reversed during spans of high sentiment. Such results were because sentiment-driven investors, under the influence of market sentiment, undermined the conventional tradeoff of risk and return during spans of high sentiment and also due to constraints on short sales. Kim and Ryu (2020) examined the capacity of investor sentiment to predict stock returns using a set of macroeconomic variables by taking term spread, exchange rate, and credit risk. The result was significant for term spread and insignificant for exchange rate and credit risk in macroeconomic variables. In this case, significant meant that the term spread variable could predict stock return in the short term, and insignificant meant that macroeconomic variables could predict stock returns in the long term. Jelilov et al. (2020) used accounting innovation tests and GJR-GARCH & GARCH models to analyze the effect of the COVID-19 outbreak on the association between equity returns and inflation in Nigeria. They found that the pandemic increased volatility and disrupted the positive relationship between the two. The study suggested that policymakers must take action to strengthen the market through collaborative efforts to mitigate the negative effects of COVID-19 on the stock market returns and inflation relationship. Sreelakshmi et al. (2022) explored the nature of the association among macro variables, equity returns, and investor sentiment during COVID-19 in India. A significant effect between investor sentiment and equity returns was observed by excluding the spans of extreme volatility. Oil prices were positive, whereas exchange rates had a negative relation with equity returns. An increase in interest rate uncertainty affected the response of equity markets negatively. Baariu and Jagongo (2022) established the relationship of selected macroeconomic variables on the Kenyan sectoral volatility index under the moderating effect of investor sentiment.

Flannery and Protopapadakis (2002) utilized the GARCH model and investigated the influence of 17 macro variables on daily equity returns. Six factors namely; Monetary Aggregates, Consumer Price Index, Balance of Trade, Producer Price Index, Housing Starts, and Employment Report, affected equity prices. Gross National Product and Industrial Production were found insignificant. Gay Jr et al. (2008) utilized the Box-Jenkins methodology (ARIMA model) and investigated the relationship of macroeconomic variables (exchange rates and oil prices) with equity prices of 4 emerging economies (China, India, Brazil, and Russia). However, no significant relationship was found between oil prices, exchange rates, and equity prices in any of the BRIC countries. This suggested that other international and domestic macroeconomic factors may have a stronger influence on these equity market returns. Additionally, the study revealed no significant relationship between past and concurrent equity market returns, indicating that the markets of these BRIC countries demonstrated weak-form market efficiency. Batten et al. (2010) employed ordinary regression and single-layer neural analysis to explore the relationship of macro factors with equity market returns under the economic uncertainty news sentiment including variables exchange rate, interest rate, crude oil prices, and the gold index for multiple countries. The results revealed that equity returns were significantly and negatively influenced by the exchange rate, the gold index, and the interest rate. Wang and Chen (2012) applied VAR models and examined the association among lagged investor sentiment, momentum, and macroeconomy and showed a significant association between them. The study also indicated that market momentum was influenced by oil prices and exchange rates and that it was possibly due to fluctuations in the US dollar caused by oil price volatility, which, in turn, affected consumers' expectations and changes in consumer expectations subsequently impacted market momentum. Singh (2016) investigated the relationship of the Wholesale Price Index, Industrial Production Index, Money Supply, Exchange Rate, and Risk-Free Rate with Indian market equity returns in the long run and found these significant. Exchange rate and industrial production showed a negative, whereas, interest rate, money supply, and wholesale price index showed a positive association with equity returns. Larsson and Haq (2016) employed the ARDL model to explore the relationship between six macroeconomic indicators namely; Michigan Consumers Sentiment Index, Personal Spending, Building Permits, M1 Money Supply, ISM Manufacturing Index, and Initial Jobless Claims and S&P 500 equity market index. Except Personal Spending, all indicators were found statistically significant in the long run over various time terms, whereas in the short run, all indicators except Money Supply (M1) exhibited significant relationships at various specified time terms. Selected indicators showed divergent characteristics based on the prevailing dynamics and economic conditions of the equity market. It is argued that investors should consider the underlying factors that drive each indicator's development rather than relying solely on individual data points. In conventional and nonconventional equity markets of Malaysia, Rashid et al. (2014) employed Two models; one used only macroeconomic variables and another incorporated both sentiment and macroeconomic factors, to investigate the association among macroeconomic variables, asset prices, and investor sentiment. The findings indicated that nonconventional equity markets, currency index, Bursa Malaysia Composite Index, and interest rates, showed a stronger impact on price movements as compared to consumer price, industrial production, investor sentiment index, and money supply. These results contributed to the ongoing debate on the importance of Sharia-compliant capital markets. Kim and Na (2018) investigated whether the findings supported the sentiment-based overpricing theory, as presented by Stambaugh et al., which still holds when considering the influence of macroeconomic conditions. After incorporating the impact of macroeconomic factors, the results no longer aligned with the sentiment-related overpricing narrative. Most risk factors were priced in response to macroeconomic conditions. It was also suggested that the original results may be attributed to the ineffective utilization of constructed investor sentiment index. As a result, it was premature to conclude that investor sentiment was the driving force behind returns observed in the anomalies. Chiu et al. (2018) applied a two-factor and structural VAR model to examine the association among investor sentiment, macro factors, and volatility, by categorizing the volatility component into persistent and transitory. Adverse shocks to aggregate supply and demand were observed that led to a rise in volatility over the long run span in the equity and bond market. Moreover, macroeconomic fundamentals were negatively affected by adverse shocks of persistent components of volatility. However, no significant association of the transitory component of volatility with the macro fundamentals was observed, whereas, a shift in investor sentiment was found to be more relevant to the transitory component. Using time series data, Khan and Khan (2018) applied the ARDL approach to examine the impact of long and short-term macro variables on equity prices in Pakistan. In the long term, exchange rates interest rates, and money supply, showed a significant effect on equity prices in the Karachi Stock Exchange, whereas, in the short term, all variables showed insignificant effects except for the exchange rate. It was recommended that the central bank should exercise caution while adjusting the money supply as excessive increases can negatively impact investment and the equity market. Additionally, the regulator should maintain relatively low-interest rates to encourage economic activities, establish a rule-based exchange rate policy to enhance the external economic environment, and avoid discretionary measures. Solanki and Seetharam (2018) claimed that the theory of Arbitrage allows for the consideration of various risk factors and can be used to model returns using either macroeconomic or microeconomic factors. A macroeconomic APT framework for nine countries was applied and included investor sentiment as a non-traditional factor and measured using the FEARS index. Through regression testing, the study found that investor sentiment was a statistically significant factor in explaining market returns in five out of the nine countries examined. These findings contributed to the existing APT research by demonstrating the importance of investor sentiment in understanding asset prices and their associated returns. Ftiti and Hadhri (2019) utilized the Decomposition Model and Non-Parametric Model to examine the relationships of investor sentiment, uncertain economic policy, and oil prices, with equity returns at various time terms. A significant causal relationship of these variables with equity returns at specific time terms is observed, Furthermore, lagged investor sentiment, oil prices, and economic policy uncertainty, showed better predictability for equity returns. Gu et al. (2021) observed that during periods of high investor sentiment, the impact of macroeconomic news on the equity market was reduced and that in times of elevated bullish sentiment, equity market reactions to macroeconomic information were weaker as compared to low sentiment periods. This effect was observed regardless of whether the macroeconomic news was either positive or negative. It appeared that investor sentiment hampered the efficient assimilation of public information into asset prices. These findings provided valuable insights into how investor sentiment influenced the relationship between fundamental factors and security prices. Seok et al. (2022) compared market sentiment on non-announced and announced dates and examined the impact of macro news based on daily and intraday investor sentiment and found that the announcements regarding macroeconomic indicators did not significantly alter the daily and intraday sentiments of investors. However, an asymmetric directional change was observed in intraday market sentiment, while no effect was observed in daily market sentiment. Baariu and Jagongo (2022) examined the association among macroeconomic variables, volatility index, and investor sentiment in the equity market and showed a divergent impact. Moreover, the impact is transmitted differently across sectors. Matar (2023) applied VECM and VAR methods and examined the association among macro variables, equity market, and non-economic factors. A long-term equilibrium relationship of macro variables with equity returns, and a significant negative impact of the Global Financial Crisis, the Iraqi invasion, the Syrian civil war, the September 11 attacks, the Gulf War, and the Amman bombing with equity returns were observed. This study supported the idea that Investors can enhance their risk-return strategies and portfolio diversification by utilizing the diverse effects of macroeconomic variables and equity market returns. Marfatia et al. (2022) utilized a dynamic model and investigated various types of uncertainty for the prediction of housing sentiment under a set of financial and economic indicators at various time terms. A significantly lower forecasted error was observed as compared to models that ignore uncertainty after incorporating measures of uncertainty in the models of housing sentiment. Moreover, uncertainty became increasingly relevant after the 2008 global financial crisis, particularly over long horizons. In ASEAN countries, Sukmadilaga et al. (2023) analyzed the impact of inflation and investor sentiment on equity returns and volatility, and it was observed that both inflation and investor sentiment significantly changed the equity returns, that in turn generated volatility in the equity markets. It also enabled investors to forecast share prices and make informed decisions, which resulted in reduced losses. By utilizing data from the equity market of Singapore, Indonesia, Malaysia, Japan, China, and South Korea, Wong and Chow (2023) explored the effect of firm-specific investor sentiment and a firm's operating performance on the relationship between macroeconomic uncertainty and equity market crash risk. In all countries, a significant positive relationship of macroeconomic uncertainty with equity price crash risk was observed and a high level of firm-specific investor sentiment strengthened the association between the two. Wang et al. (2023) applied Quantile Regression and Variational Mode Decomposition and analyzed the response of BRICS countries' equity markets to external and internal macroeconomic shocks under varied investment and market states. Each factor showed a significant and varied effect on equity prices under varied market states. Moreover, macro variables and equity prices exhibited distinct behavior during the 2008 financial crisis as compared to normal periods. Zargar and Kumar (2023) verified the spillover effects of investor uncertainty, mood, sentiment, and fear on the US tourism sectoral returns and exposed that shocks in the financial market were sourced by investor fear, mood, and sentiment, while the recipient of these shocks was economic uncertainty. Sharma et al. (2023) examined the relationship between the Wholesale Price Index, Effective Exchange Rate, Industrial Index, Crude Oil Prices, and Money Supply with indices (CARBONEX and GREENEX) of sustainability in India and observed that the GREENEX index was significantly influenced by the M3, Crude Oil Prices, Industrial Production index, and Wholesale Price Index, whereas the CARBONEX index was significantly influenced by M3, Crude Oil Prices, and Industrial Production index, but not by Wholesale Price Index. Furthermore, GREENEX and CARBONEX did not affect by interest rates. Van Eyden et al. (2023) applied 'Panel Regression Analysis with Heterogeneous Coefficients' and 'Multi-Scale Confidence Indicator with Singularity Law Power of Log Periods' and identified bearish and bullish bubble spans and the influence of consumer and business sentiment on the G7 equity markets. Investor sentiment showed a significant impact in the reduction of bearish and progression of bullish bubbles over long and short-run spans. The study also claimed that a collapse or improvement in investor sentiment could lead to market crashes or recoveries in bull or bear markets, therefore, investors and policymakers need consideration in this regard.

2.21 COVID, Investor Sentiment, and Market Returns

Zhaohui (2005) investigated the investor's sentiment effect on equity market crises, contrary to standard finance theory that considered stock prices to reflect the discounted value of expected cash-flows, and those arbitrageurs eliminated irrationalities. The behavioral approach suggested that waves of irrational sentiment could persist and affect asset prices, eventually leading to crises. Hudomiet et al. (2011) examined the impact of the 2008 stock market crash on the expectations of households regarding stock market returns. Results indicated a temporary average increase in expectations and uncertainty. A long-term increase in disagreement, particularly among stockholders, the more informed investors, and those with higher cognitive capacity, was also observed. The increase in disagreement co-moved with trading volume and market volatility. Huerta and Perez-Liston (2010) examined the impact of hurricanes on investor sentiment and equity returns by utilizing an event study approach and found that equity returns significantly decreased on the same day and one day before the hurricane made landfall and that not all industries were affected equally. Large firms were the least impacted. On the day of landfall, a significant increase in fear and a significant decrease in investor sentiment was observed a week before landfall. Moreover, they found that hurricanes had a negative impact on investor sentiment as well as equity market returns. Shan and Gong (2012) examined the effect of investor sentiment on equity returns after the 'Wenchuan Earthquake' in China and found that firms closer to the epicenter experienced lower returns in the subsequent 12 months after the earthquake. Ferrer et al. (2016) used data from European and US markets to explore the relation of consumer confidence indices with movements of equity markets and found that this index did not have a universally positive relation with equity returns. Further, an indirect relationship between consumer expectations and fluctuations in equity markets was observed. Jiang et al. (2019) investigated the impact of extreme weather conditions on the equity returns of Shenzhen and Hong Kong exchanges. It was found that extreme weather conditions significantly affected the Shenzhen Exchange, but this effect was weakened after the QFII program. Further, foreign investors reduced the effect of local weather conditions on returns.

Liu et al. (2020b) used an event study approach to analyze the short-term influence of COVID-19 on indices of 21 global equity markets and found significant negative excess returns in affected countries, specifically in Asia, after the pandemic outbreaks. Fixed Effect Panel Regression also verified that confirmed cases had an adverse effect on abnormal returns by exacerbating investors' pessimistic sentiment and fear of uncertainties. Mishra and Mishra (2020) investigated the economies of Asian equity markets affected by the COVID-19 pandemic and found that differences in demand and supply side shocks created spring-like a downturn in almost all financial and economic sectors. Asian stock markets experienced volatility clustering, mainly driven by investors' pessimistic and panic sentiments, as well as changes in oil prices, exchange rates, and the strength of COVID-19 cases.

Ryu et al. (2020) investigated the effect of product market competition on the relationship between equity returns and investor sentiment and the way financial crises affected this relationship. The results showed that low product market competition had weakened the relationship and remained significant during financial crises. Liu et al. (2020a) analyzed the effect of climate change and epidemic disease on investor sentiment and, finally, on equity returns. They developed an investor sentiment composite index using principal component analysis and applied regression models to investigate its influence on current and near-term future stock returns in different market states. There was a significant positive effect of investor sentiment on equity returns during the total period, bull market, and neutral market, with the greatest influence during the bull market. When the market was in an upward trend, investors were willing to put funds into the stock market, leading to the Bandwagon effect and deviation from fair prices. Zhai et al. (2022)

investigated the effect of COVID-19 on equity returns in China during the lockdown in Wuhan City and explored the role of corporate social responsibility in mitigating the adverse effect of pessimistic investor sentiment. They observed that firms close to and in the Hubei province exhibited more negative cumulative abnormal returns than firms farther away from the epicenter. Furthermore, firms with strong CSR activities, such as corporate donations, experienced a less adverse impact on their stock returns than those with no or weak CSR activities, indicating that CSR functioned as insurance to alleviate negative investor sentiment. Yahya et al. (2021) explored the relationship between investor attention, investor sentiment, COVID-19 cases, social isolation, and equity returns in the markets of Germany by applying Dynamic Panel Model. There was a significant negative effect of increased COVID-19 cases on investors' sentiment and, in turn, on equity returns. However, recovered cases increased the attention and sentiment of investors and, in turn, increased equity returns. The ability of investors to make better decisions was also improved due to social isolation. Wu et al. (2016) conducted an event study and examined the impact of COVID-19 on the Chinese equity market and found a significant negative effect after the event. Individual investor sentiment had a strong positive relation with equity returns during regular periods, which was stronger for certain industries and firms.

Jabeen et al. (2021) applied the Long Short Term Memory approach to improve accuracy in predicting market returns influenced by investor sentiment in the presence of coronavirus. The researcher applied 'Mean Squared Error,' 'Mean Absolute Error,' and 'Root Mean Squared Error' to reach a conclusion and observed that using coronavirus event sentiments and the LSTM prediction model improved performance. Chen et al. (2021) concluded that COVID-19 affected equity returns as well as equity prices. Public attention decreased (increased) equity market response to firm-specific information. The decreasing effect of public attention was strong to positive information. Price reversal was observed following public attention. Subramaniam and Chakraborty (2021) used Google Trends Search Volume Index and constructed COVID-19 fear index to analyze the effect of the pandemic outbreak on equity returns and found a persistent negative relationship between the two. Anastasiou et al. (2022) constructed a positive search volume index to examine the relationship between investor sentiment and returns of the G20 countries during the COVID-19 outbreak. They found a decrease in the crisis sentiment of investors with an increase in the COVID-19 index and that investor sentiment could predict equity returns and volatility even during the pandemic outbreak. Debata et al. (2021) used the nonlinear causality technique in combination with the wavelet coherence technique and analyzed the association between equity market returns and pandemic sentiment in India. The strong correlation between pandemic sentiment and stock returns was observed at all-time frequencies, and this correlation was at the peak in the initial stages and gradually decreased with time. Agarwal and Vats (2021) used Fractal Dimension Analysis to investigate patterns and structures in stock market data around crashes. They found a measurable change in market predictability and persistence levels around crash points, which could devastate the economy and investors. These findings could serve as warning signals for an impending crisis and assist investors, traders, and speculators in the stock market. Yaşar (2021) analyzed the BIST Tourism Index return volatility to study the effect of COVID-19 on the tourism industry of Turkey by taking into account various economic factors. A significant correlation was found among economic sentiment, return volatility of the BIST Tourism index, new cases, and health and containment index. Xu et al. (2021) studied the effect of COVID-19 on the returns of the Chinese equity market. They found that the outbreak negatively affected stock returns and influenced price sensitivity to firm-specific information. The study also identified varying effects based on the scale of infection and public attention toward the pandemic. Public attention was found to accelerate the stock market response to firm-specific information, while the infection scale decelerated it. The study observed price reversal and momentum following changes in public attention and infection scale. Möller and Reichmann (2023) analyzed over 500,000 15-second transcribed audio snippets from major US TV stations throughout 2020 that mentioned COVID-19. Using unsupervised machine learning, they identified seven topics discussed in the US TV news related to COVID-19. They found that changes in airtime corresponding to certain COVID-19-related topics predicted significant market reactions the following day, particularly for the stock market topic. This effect induced temporary upward price pressure followed by return reversals in subsequent days, which was more pronounced after the market collapsed in March 2020 and concentrated in certain industry portfolios. These findings suggested that TV news about the stock market during COVID-19 fueled investor fears of losing gains. Debata et al. (2021) constructed a pandemic sentiment index using Textual Analysis of newspaper headlines and the Intensity of Google Search Volumes using wavelet coherence and nonlinear causality techniques and examined the relation of the newly constructed index on equity returns of India. During the pandemic, a high relationship between PS and equity returns was found in all time-frequency domains. During the initial months, this relationship was more strong, which gradually decreased. Hamal and Gautam (2021), by a systematic review of 40 publications, identified the effect of COVID-19 on the performance of the equity market and the government's response in this regard. They observed that both the pandemic and government policies adversely affected the equity market's volatility in the short run. This adverse effect gradually decreased, and the markets stabilized eventually. The government's targeted response and investor sentiment boosted investors' confidence in the market.

Min et al. (2022) analyzed the combined effect of COVID-19 and investor sentiment on 3 stock indices of South Korean real estate industries and observed that the REIT sector was less sensitive to COVID-19 impacts as compared to the other two indices and that earlier information on REITs explained changes in the time series process. The study suggested that REITs could provide substantial benefits of diversified investment even in short-term market disruptions. Bissoondoyal-Bheenick et al. (2022) examined the asymmetric effect of investor sentiment on equity returns and volatilities on a daily and monthly basis during the US and China trade war. Investor sentiment had a negative effect on both return and volatility. This impact was more pronounced during the spans of bearish markets. Goel and Dash (2022) applied panel regression on data from 53 countries to explore the moderating role of government policy interventions on the relationship between equity returns and investor sentiment during COVID-19 and found that interventions of government had a moderating effect on the relationship between the two. Further, effectiveness in government policy interventions mitigated the influence of investors' sentiment on returns.

Researchers had found that social media data could be valuable in understanding the behavior of financial assets, particularly when analyzing the sentiment expressed by users on these platforms. Based on the idea, de Sousa-Gabriel et al. (2023) examined the way, in what way investor sentiment derived from social media influenced green investments and whether this influence was either dependent on time. The study also considered the epidemic and the Russian war with Ukrainian in shaping the relationship. The findings of the study revealed distinct patterns of behavior during different periods, indicating that the proximity of green investments and investor sentiment varied over time. During shorter periods (pandemic crisis), sentiment consistently emerged as a risk factor in environmental investments. Moreover, it highlighted the significance of information spawned on social media in pricing ecological assets, however, over long spans, the study did not identify any shared stochastic trends. This suggested that the mechanisms driving these series exhibited a certain degree of autonomy, indicating that other factors beyond sentiment played a more prominent role in shaping long-term trends in environmental investments. Mundi and Yadav (2023) focused on different time horizons of investors and examined the reactions of share markets in response to COVID-19 and market sentiment among NIFTY 50 firms of India by utilizing event study and wavelet coherence analysis during the first and second waves of the pandemic. It was revealed that market sentiment reflecting positive and negative sentiment were negatively and positively correlated with COVID-19 during the first wave, respectively for up to 16 days. When examining abnormal returns during both waves, statistically significant negative abnormal returns were observed only during the first wave. Ammari et al. (2023) derived from Twitter an investor sentiment index and used 'Panel Smooth Transition Regression' to look into the association among stock liquidity, the death rate caused due to the outbreak, and investor sentiment. The influence of Twitter sentiment on stock liquidity was observed as nonlinear and varied across time and firms based on the death rate from the pandemic in the United States. A threshold level of 4.32% of the death rate was calculated, above which investor sentiment positively affected stock liquidity, and the transition from a low to a high pandemic death rate regime was found to occur abruptly rather than gradually, indicating significant shifts in investor perception. **?** developed the 'Twitter Financial Sentiment Index by employing the 'Natural Language Processing approach' to explore its relationship with expected returns and bond spread and found a strong linkage concerning bond spread. It was also observed that 'Overnight Financial Sentiment' was able to predict the next day's returns but was unable to predict a day before returns earlier an announcement. The findings collectively underscored the usefulness of sentiments in understanding and forecasting financial market dynamics. Xu et al. (2023) divided market sentiment regarding the pandemic into predictable and unpredictable sentiments and examined the impacts of these components on the equity markets. Unpredicted sentiment showed a greater influence on the fluctuations as compared to the predicted sentiment of equity markets, however, unpredicted sentiment did not affect the informativeness of these markets, despite the significant impact of predicted sentiment in the provision of valuable information. Furthermore, the estimated sentiment was informative and contributed to market dynamics, while unanticipated sentiment tended to be noisy and had a detrimental impact on market information.

Bhattacharjee and De (2023) employed a Markov-Switching technique to look into the association between the evolving policy response to the equity market sentiment and outbreak-19 in India using the Indian VIX, which served as a measure of market sentiment, and the Government Response Index. Policy response revealed a positive association with market sentiment during fearful market spans and high and low-level fear spans of market sentiment were observed as short-lived suggesting potential speculation and heightened volatility in the Indian equity market during the outbreak.

To explore the asymmetric impact of outbreak announcements on sentiment of investors in the equity market, Mili et al. (2023) considered five investor sentiment indicators and decomposed outbreak indicators into negative and positive and utilized the NARDL model. Announcements of outbreak cases revealed a greater influence on investor sentiment as compared to announcements of deaths and the significant short and long-term impacts of these announcements on investor sentiment. Furthermore, the research found asymmetries and nonlinearities in this relationship, particularly with respect to the short and long run. Notably, negative news regarding COVID-19 showed a stronger connection with investor sentiment.

The review of the literature reveals that the influence of investor sentiment on equity market returns is not consistent and uniform, and this inconsistency in results can be attributed to innate market integrity and herding behavior of investors in the market (Schmeling, 2007, 2009), non-linear/random patterns of stock prices (Wang et al., 2013), cultural aspects of the market as well as investors behavior (Chiu et al., 2008), frequency of data and models of study involved (Gric et al., 2021), methodologies used (Chakraborty and Subramaniam, 2020; Gebka, 2014), investor sentiment regimes (Baker and Wurgler, 2006; He et al., 2020; Lutz, 2016; Namouri et al., 2018), and moods of investors in countries (Abudy et al., 2022). Due to these conflicting results, this study revisits the non-linear relationship between optimistic investor sentiment and pessimistic investor sentiment and equity market returns using advanced methods in emerging markets.

2.22 Hypotheses of the Study

From the review of the literature, it is concluded that there is no consensus among researchers in establishing the relationship between investor sentiment and equity returns. The variations found in the results of the research may be due to variations in the methodologies, geographic areas, measurement tools and techniques, and time spans. Therefore, this study re-examines the relationship between investor sentiment and equity returns by constructing and testing the following hypotheses:

H_1: A non-linear relationship exists between investor sentiment and contemporaneous equity returns.

H_{2a}: Investor sentiment positively affects stock return in the short term.

H_{2b}: Investor sentiments have a negative effect on stock return in the long term.

H_{3a}: There is a positive relationship between positive investor sentiment with equity returns.

H_{3b}: There is a positive relationship between negative investor sentiment with equity returns.

H_{4a}: Positive relationship exists between a moderate level of investor sentiment and stock return.

H_{4b}: Negative relationship exists between the extreme levels of investor sentiment and stock return.

H_5: An asymmetric relationship exists between investor sentiment and conditional volatility.

H_6: Market risk negatively correlates with expected stock return during a high sentiment period.

H_7: A change in the macroeconomic environment influences the relationship between different states of investor sentiment and stock return.

H_8: Stock returns are influenced by investor sentiment during an epidemic.

Chapter 3

Data Description and Methodology

This chapter provides a methodological and procedural description of the present study including, sample selection, sources of data collection, and econometric models.

This study is aimed with certain objectives (a) to explore the non-linear relation of investor sentiment with contemporaneous equity returns, (b) to determine the predictive power of investor sentiment for equity returns over short and long horizons, (c) to examine the role of optimistic and pessimistic investor sentiment on equity returns, (d) to observe the role of extremely optimistic and extremely pessimistic investor sentiment on equity returns, (e) to investigate the role of positive and negative investor sentiment on volatility, (f) to analyze the role of divergent levels of investor sentiment on the relationship between market risk and equity returns, (g) to observe the change in investor sentiment and its impact on the relationship between macro variables and equity returns, and (h) to study the relationship between investor sentiment and equity returns during pandemic COVID-19. To capture the empirical status of the elaborated hypotheses, Auto-Regressive Models are applied at country level whereas Dynamic Panel Models are applied at group-level. These models are applied due to the reason that it predicts better and address the issues of autocorrelation and endogeneity.

3.1 Population and Sample

The population consists of emerging equity markets. The sample consists of Brazil, Russia, Indonesia, India, China, South Africa, and Pakistan (BRIICSP).

These countries represent emerging markets where the investors are supposed to be more irrational and therefore the asset prices in these markets are more susceptible to the effect of changes in investor sentiment.

Each sampled country has many stock markets and indices, this study considers only a representative index for each country in the sample.

The list of representative sample indexes for each country is given below:

Country	**Representative Country Market Index**	**Acronym for Representative Index**
Brazil	Brazilian Stock Exchange Index (Bolsa de Valores de São Paulo)	BOVESPA
Russia	Russia Trading System Index	RTSI
Indonesia	Jakarta Stock Exchange Composite Index	JCI
India	National Stock Exchange of India Index	NSEI Nifty 50
China	Shanghai Composite Index	SHCOMP
South Africa	Johannesburg Stock Exchange Index	JSEI
Pakistan	Karachi Stock Exchange Index	KSE-100

In this study, secondary data is used to capture the long-term effects, as many studies prefer secondary data because it eliminates the reliability challenges and biases that arise in survey data (Banchit et al., 2020).

Secondary data for daily share prices, outstanding shares, and trading volume is collected from representative stock markets. Data about the 'no of shares' is collected against each firm listed on the particular index.

Data for risk-free rates, bonds rates, and Industrial Production Index rates are collected mainly from the world data bank, OECD, and the websites of central banks of selected countries. VaR and C-VaR are measured using 30 days average at both 95% and 99% confidence level.

The data is collected from the representative indices from the year 2001 to 2020. This period was selected for study because, in many of the sample indices, the data before 2001 was not available on the sources used for this study.

3.2 Extraction of Market Returns

3.2.1 Daily share prices of each index are converted into returns by using the formula;

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

Where ln is the natural log, R_t is the return of daily prices of the selected index, P_t is the price of the selected index at time t, $P_{(t-1)}$ is the price of the selected index at first lag.

3.2.2 Conversion of Data of Macroeconomic Variables from Monthly to Daily Basis

Data on macroeconomic variables are available on a monthly basis whereas the data related to other variables is available on a daily basis. To create uniformity in the data monthly data is converted to daily basis.

3.3 Construction of Investor Sentiment Index

Two proxies (a) Trading Volume (as used by Baker and Stein (2004); Banchit et al. (2020)) and (b) Turnover Ratio (as used by Baker and Wurgler (2006)) are used to measure investor sentiment. The Principal Component Analysis approach of Baker and Wurgler (2006, 2007) is applied to construct an investor sentiment index by using two equations; first for each country included in the study and second for all countries collectively.

The equation used to create an index for individual countries is:

$$SENT_t = \beta_0 + \beta_1 T_t + \beta_2 R_t + \varepsilon_t \tag{2}$$

Where SENT_t is the sentiment index at the country level, T_t is trading volume and R_t is the turnover ratio. β_1 And β_2 are the coefficients of trading volume and turnover ratio.

The equation used to create an index for a group of countries is:

$$SENT_{i,t} = \beta_0 + \beta_1 T_{i,t} + \beta_2 R_{i,t} + \varepsilon_{i,t} \tag{3}$$

Where $\mathrm{SENT}_{i,t}$ is the sentiment index for the group of countries, $\mathrm{T}_{(i,t)}$ is trading volume and $\mathrm{R}_{(i,t)}$ is the turnover ratio of country 'i' for time 't'.

3.3.1 Impact of Investor Sentiment on Contemporaneous Equity Returns

The impact of investor sentiment on Contemporaneous market returns in linear and non-linear settings is calculated separately for the country at an individual level and countries at a group level.

For the country at an individual level the equation used is:

$$R_{t+0} = \beta_0 + \beta_1 SENT_t^{*} + \beta_2 SENT_t^{*2} + \beta_3 RF_t + \beta_4 TS_t + \beta_5 IPI_t + \beta_6 AR_{t-1} + \varepsilon_t \tag{4}$$

Where R_{t+0} are current-day index returns, $SENT_t^*$ is the investor sentiment index calculated from the PCA method, $SENT_t^{*2}$ is the non-linear term, $RF_t, TS_t,\ IPI_t$ are macroeconomic variables represent risk-free rate, term spread, and industrial production index respectively.

These variables are supposed as predictors of market returns and thus are frequently used by researchers. AR_t is Auto Regressive term. β_1 And β_2 are coefficients that indicate investor sentiment for linear and nonlinear terms respectively.

For countries at the group level, the equation used is:

$$R_{t+0} = \beta_0 + \beta_1 SENT_{i,t}^* + \beta_2 SENT_{i,t}^{*2} + \beta_3\, RF_{i,t} + \beta_4\, TS_{i,t} + \beta_5\, IPI_{i,t} + \beta_6\, AR_{i,t-1} + \varepsilon_{i,t} \tag{5}$$

Where R_{t+0} is stock index returns on the current day, $SENT_{i,t}^*$ is the investor sentiment index calculated from the PCA method, $SENT_{i,t}^{*2}$ is the non-linear term of an index, $RF_{i,t}, TS_{i,t},\ IPI_{i,t}$ are macroeconomic variables representing risk-free rate, term spread and industrial production index respectively at group level. $AR_{i,t}$ is Auto Regressive term.

3.4 Investor Sentiment and Market Returns

The predictive power of investor sentiment for stock market returns in linear and nonlinear settings over short and long horizons at the country and group level is examined by using the models:

Predictive model at the country level:

$$R_{t+n} = \beta_0 + \beta_1 SENT_t^* + \beta_2 SENT_t^{*2} + \beta_3\, RF_t + \beta_4\, TS_t + \beta_5\, IPI_t + \beta_6\, AR_{t-1} + \varepsilon_t \tag{6}$$

Where R_{t+n} is the stock index return at the country level at the time (t+n). For each country the value of n is 1,5,10 and 20 days for the short term; 40,60,180 and 240 days for the long term as used by Kim (2020). $SENT_t^*$ is used for prediction in linear terms whereas $SENT_t^{*2}$ is used for nonlinear terms.

Predictive model for group level:

$$R_{i,t+n} = \beta_0 + \beta_1 SENT_{i,t}^* + \beta_2 SENT_{i,t}^{*2} + \beta_3\, RF_{i,t} + \beta_4\, TS_{i,t} + \beta_5\, IPI_{i,t} + \beta_6\, AR_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

Where $R_{i,t+n}$ is the stock index return at the time (t+n). The value of n is 1,5,10 and 20 days for the short term; 40,60,180 and 240 days for the long term as used by Kim (2020). $SENT_{i,t}^*$and $SENT_{i,t}^{*2}$ are used for prediction in linear and nonlinear terms respectively.

3.4.1 Impact of Optimistic and Pessimistic Investor Sentiment on Equity Market Returns

To calculate the non-linear and linear effect of optimistic investor sentiment and pessimistic investor sentiment on the equity market returns at the country and group level two models are used. The values of the created investor sentiment index with positive signs are taken as optimistic investor sentiment whereas the values with negative signs are taken as pessimistic investor sentiment.

For country-level analysis following Auto-Regressive Model is used:

$$R_t = \beta_0 + \beta_1 SENT_t^* * D_{1,\,t} * + \beta_2 SENT_t^* * D_{2,\,t} + \beta_3 SENT_t^{*2} * D_{1,t} + \beta_4 SENT_t^{*2} * D_{2,\,t} + \beta_5 RP_t + \beta_6 AR_{t-1} + \beta_7 AR_{t-2} + \varepsilon_t \tag{8}$$

Where R_t denotes stock index returns, $SENT_t^* * D_{1\,t}$ and $SENT_t^* * D_{2\,t}$, represents linear terms for optimistic and pessimistic investors respectively, $SENT_t^{*2} * D_{1\,t}$

is the non-linear term for optimistic investor sentiment, $SENT_t^{*2} * D_{2\,t}$ is for pessimistic investor sentiment, RP_t denotes market premium which is supposed a predictor of market returns. β_6 and β_7 are coefficients of Auto-Regressive terms at the country level.

For group-level analysis following Dynamic Panel Model is used:

$$R_{i,t} = \beta_0 + \beta_1 SENT_{i,t}^{*} * D_{1,\,i,t}* + \beta_2 SENT_{i,t}^{*} * D_{2,\,i,t} + \tag{9}$$

$$\beta_3 SENT_{i,t}^{*2} * D_{1,\,i,t} + \beta_4 SENT_{i,t}^{*2} * D_{2,\,i,t} + \beta_5 RP_{i,t} + \beta_6 AR_{i,t-1} + \beta_7 AR_{i,t-2} + \varepsilon_{i,t}$$

Where $R_{i,t}$ denotes equity market returns for group level, $SENT_{i,t}^{*}$, $SENT_{i,t}^{*} * D_{2\ i,t}$, $SENT_{i,t}^{*2} * D_{1\ i,t}$ and $SENT_{i,t}^{*2} * D_{2\ i,t}$ are linear and non-linear terms for optimistic investor sentiment and for pessimistic investor sentiment respectively, $RP_{i,t}$ denotes market premium which is supposed as predictors of market returns. β_6 and β_7 are coefficients of Auto-Regressive terms at the group level.

3.5 The Effect of Moderate and Extreme Levels of Investor Sentiment on Equity Returns

3.5.1 Impact of Moderate and Extreme Levels of Investor Sentiments on Returns at the Country Level

The created Investor sentiment index is categorized into extremely optimistic, moderate, and extremely pessimistic.

The extremely positive and extremely negative investor sentiments are calculated in three steps by using dummy variables D_O and D_P with the threshold of $\Delta SENT_O$ *and* $\Delta SENT_P$.

In the first step extremely optimistic investor sentiment is calculated by using the formula.

$$D_O = \begin{cases} 0, & if\ \Delta SENT_t < \Delta SENT_O; \\ 1, & if\ \Delta SENT_t \geq \Delta SENT_O; \end{cases}$$

Where $\Delta SENT_O$ represents extremely optimistic sentiment. $D_O = 1$ unless the change in investor sentiment is more than the limit of $\Delta SENT_O$. $D_O = 0$, unless the change in investor sentiment is less than the limit of $\Delta SENT_O$.

In the second step, pessimistic sentiment is calculated by using the following equation.

$$D_P = \begin{cases} 0, & if\ \Delta SENT_t > \Delta SENT_P; \\ 1, & if\ \Delta SENT_t \leq \Delta SENT_P; \end{cases}$$

Where $\Delta SENT_P$ represents extremely pessimistic sentiment. $D_p = 1$ unless the change in investor sentiment is lower than the limit of $\Delta SENT_P$. $D_p = 0$, unless the change in investor sentiment is greater than the limit of $\Delta SENT_P$.

In the third step these dummy variables are used for the calculation of investor sentiment swings. $(\Delta SENT_t - \Delta SENT_{O,t}) * D_{O,t}$ This interaction term is used to indicate the extremely optimistic investor sentiment whereas this $(\Delta SENT_t - \Delta SENT_{P,t}) * D_{P,\ t}$ interaction term is used to indicate the extremely pessimistic investor sentiment.

At the country level, the impact of extremely positive, moderate, and extremely negative investor sentiment on equity returns is examined by using the following equation:

$$\begin{aligned} R_t &= \beta_0 + \beta_1 \Delta SENT_t + \beta_2 \left(\Delta SENT_t - \Delta SENT_{O,t}\right) * D_{O,t} + \\ &\quad \beta_3 \left(\Delta SENT_t - \Delta SENT_{P,t}\right) * D_{P,\ t} + \beta_4 AR_{t-1} + \varepsilon_t \end{aligned} \tag{10}$$

R_t represents country returns, $\Delta SENT_t$ measures moderate level of investor sentiment at country level, $(\Delta SENT_t - \Delta SENT_{O,t}) * D_{O,t}$ measures the extremely optimistic level of investor sentiment conditioned with, if it is greater than the threshold bound of $\Delta SENT_O$. $(\Delta SENT_t - \Delta SENT_{P,t}) * D_{P,\ t}$ measures extremely pessimistic level of investor sentiment conditioned with, if it is less than the limit of $\Delta SENT_P$. If coefficient of $(\beta_1 + \beta_2) < 0$ it means that extremely pessimistic investor sentiment will move the prices toward fundament value after reaching at higher levels and if $\beta_1 > 0$ and $(\beta_1 + \beta_3) < 0$ it will also indicate that extremely pessimistic will also revert prices toward fair prices at reaching lower levels.

3.5.2 Impact of Moderate and Extreme Levels of Investor Sentiments on Returns at Group Level

At the group level, the impact of moderate, extremely positive, and extremely negative investor sentiment on equity returns is calculated by using the following equation:

$$\begin{aligned} R_{i,t} \ &= \beta_0 + \ \beta_1 \Delta SENT_{i,t} + \beta_2 \left(\Delta SENT_{i,t} - \Delta SENT_{O\ i,t} \right) * D_{O\ i,t} + \\ &\quad \beta_3 \left(\Delta SENT_{i,t} - \Delta SENT_{P\ i,t} \right) * D_{P\ i,t} + \beta_4 AR_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{11}$$

$R_{i,t}$ represents group returns, $\Delta SENT_{i,t}$ represents the effect of moderate level of investor sentiment at group level, $(\Delta SENT_{i,t} - \Delta SENT_{O,i,t}) * D_{O,i,t}$ represents the impact of extremely optimistic level of investor sentiment and conditioned, if it is greater than the threshold bound of $\Delta SENT_{O\ i,t}$, $(\Delta SENT_{i,t} - \Delta SENT_{P,i,t}) * D_{P\ i,t}$ estimates the impact of extremely pessimistic level of investor sentiment if it is less than the limit of $\Delta SENT_P$ and if $(\hat{a}_1 + \beta_2) < 0$ it means that when investor sentiment is extremely optimistic it exerts a reversal effect on returns. if $\beta_1 > 0$ and $(\beta_1 + \beta_3) < 0$ it means that when investor sentiment is extremely pessimistic it also exerts a reversal effect on returns.

3.6 Impact of Positive and Negative Investor Sentiment on Conditional Volatility

The non-linear and linear effect of positive investor sentiment and negative investor sentiment on the conditional volatility is calculated by using the following models:

3.6.1 For country-level analysis the following model is used:

$$Volatility_t = \beta_0 + \beta_1 SENT_t^{*} * D_{1,\ t} * + \beta_2 SENT_t^{*} * D_{2,\ t} + \beta_3 SENT_t^{*2} * D_{1,t} + \beta_4 SENT_t^{*2} * D_{2,\ t} + \beta_5 RP\ _t + \beta_6 AR_{t-1} + \beta_7 AR_{t-2} + \beta_8 MA_{t-1} + \varepsilon_t \quad (12)$$

Where $Volatility_t$ is conditional volatility, $SENT_t^{*2} * D_{1,\ t}$ is the non-linear term for positive investor sentiment, $SENT_t^{*2} * D_{2\ t}$ is for negative investor sentiment, RP_t denotes market premium which is supposed a predictor of market returns. β_6 and β_7 are coefficients of Auto-Regressive terms at the country level. β_8 is the coefficient of the Moving-Average term at the country level.

3.6.2 For group-level analysis the following model is used:

$$Volatility_{i,t} = \beta_0 + \beta_1 SENT_{i,t}^{*} * D_{1\ i,t} * + \beta_2 SENT_{i,t}^{*} * D_{2\ i,t} + \beta_3 SENT_{i,t}^{*2} * D_{1,i,t} + \beta_4 SENT_{i,t}^{*2} * D_{2\ i,t} + \beta_5 RP\ _{i,t} + \beta_6 AR_{i,t-1} + \beta_7 AR_{i,t-2} + \varepsilon_{i,t} \quad (13)$$

Where $Volatility_{i,t}$ is conditional volatility for a group level, $SENT_{i,t}^{*2} * D_{1\ i,t}\ and\ SENT_{i,t}^{*2} * D_{2\ i,t}$ are linear and nonlinear terms for positive investor sentiment and negative investor sentiment, $P_{i,t}$ denotes market premium which is supposed as predictors of market returns.

3.7 The Role of Investor Sentiment on the Relationship Between Market Risk and Returns

The sentiment index is divided into high and low sentiment periods. The values of the created investor sentiment index with positive signs are defined as high sentiment periods of investor sentiment whereas the values with negative signs are defined as low sentiment periods of investor sentiment. To measure market risk VaR and CVaR are used at 95% and 99% confidence levels following equations are used;

3.7.1 For VaR95 at the country level:

$$R_t = \beta_0 + \beta_1 VaR95_t + \beta_2 \Delta SENT_t * D_t + \beta_3 \Delta SENT_t * (1 - D_t) + \beta_4 VaR95_t * \Delta SENT_t * D_t + \beta_5 VaR95_t * \Delta SENT_t * (1 - D_t) + \beta_6 AR_{t-1} + \varepsilon_t \quad (14)$$

3.7.2 For VaR95 at the group level:

$$R_{i,t} = \beta_0 + \beta_1 VaR95_{i,t} + \beta_2 \Delta SENT_{i,t} * D_{i,t} + \beta_3 \Delta SENT_{i,t} * (1 - D_{i,t}) + \beta_4 VaR95_{i,t} * \Delta SENT_{i,t} * D_{i,t} + \beta_5 VaR95_{i,t} * \Delta SENT_{i,t} * (1 - D_{i,t}) + \beta_6 AR_{i,t-1} + \varepsilon_{i,t} \quad (15)$$

3.7.3 For VaR99 at the country level:

$$R_t = \beta_0 + \beta_1 VaR99_t + \beta_2 \Delta SENT_t * D_t + \beta_3 \Delta SENT_t * (1 - D_t) + \beta_4 VaR99_t * \Delta SENT_t * D_t + \beta_5 VaR99_t * \Delta SENT_t * (1 - D_t) + \beta_6 AR_{t-1} + \varepsilon_t \quad (16)$$

3.7.4 For VaR99 at the group level:

$$R_{i,t} = \beta_0 + \beta_1 VaR99_{i,t} + \beta_2 \Delta SENT_{i,t} * D_{i,t} + \beta_3 \Delta SENT_{i,t} * (1 - D_{i,t}) + \beta_4 VaR99_{i,t} * \Delta SENT_{i,t} * D_{i,t} + \beta_5 VaR99_{i,t} * \Delta SENT_{i,t} * (1 - D_{i,t}) + \beta_6 AR_{i,t-1} + \varepsilon_{i,t} \quad (17)$$

3.7.5 For CVaR95 at the country level:

$$R_t = \beta_0 + \beta_1 CVaR95_t + \beta_2 \Delta SENT_t * D_t + \beta_3 \Delta SENT_t * (1 - D_t) + \beta_4 CVaR95_t * \Delta SENT_t * D_t + \beta_5 CVaR95_t * \Delta SENT_t * (1 - D_t) + \beta_6 AR_{t-1} + \varepsilon_t \quad (18)$$

3.7.6 For CVaR95 at the group level:

$$R_{i,t} = \beta_0 + \beta_1 \; CVaR95_{i,t} + \beta_2 \Delta SENT_{i,t} * D_{i,t} + \beta_3 \Delta \quad (19)$$
$$SENT_{i,t} * (1 - D_{i,t}) + \beta_4 \; CVaR95_{i,t} * \Delta SENT_{i,t} * D_{i,t} + \beta_5$$
$$CVaR95_{i,t} * \Delta SENT_{i,t} * (1 - D_{i,t}) + \beta_6 AR_{i,t-1} + \varepsilon_{i,t}$$

3.7.7 For CVaR99 at the country level:

$$R_t = \beta_0 + \beta_1 \; CVaR99_t + \beta_2 \Delta SENT_t * D_t + \beta_3 \Delta SENT_t * (1 - D_t) + \quad (20)$$
$$\beta_4 CVaR99_t * \Delta SENT_t * D_t + \beta_5 \; CVaR99_t * \Delta SENT_t * (1 - D_t) + \beta_6 AR_{t-1} + \varepsilon_t$$

3.7.8 For CVaR99 at the group level:

$$R_{i,t} = \beta_0 + \beta_1 \; CVaR99_{i,t} + \beta_2 \Delta SENT_{i,t} * D_{i,t} + \beta_3 \Delta \quad (21)$$
$$SENT_{i,t} * (1 - D_{i,t}) + \beta_4 \; CVaR99_{i,t} * \Delta SENT_{i,t} * D_{i,t} + \beta_5$$
$$CVaR99_{i,t} * \Delta SENT_{i,t} * (1 - D_{i,t}) + \beta_6 AR_{i,t-1} + \varepsilon_{i,t}$$

Where R_t denotes returns at the country level, $R_{i,t}$ represents returns at the group level, $\Delta SENT_t$ represents the investor sentiment index at the country level, $\Delta SENT_{i,t}$ represents investor sentiment index at group level, D_t represents the high level of investor sentiment at country level, $(1 - D_t)$ represents a low level of investor sentiment at country level, $D_{i,t}$ represents the high level of investor sentiment at the group level, $(1 - D_{i,t})$ represents a low level of investor sentiment at group level.

The interaction term $(VaR_t * \Delta SENT_{i,t} * D_t)$ represents the rising trend of investor sentiment at the country level, $(VaR_t * \Delta SENT_t * (1 - D_t))$ represent the falling trend of investor sentiment at country level, $(VaR_{i,t} * \Delta SENT_{i,t} * D_{i,t})$ represents the rising trend of investor sentiment at group level, $(VaR_{i,t} * \Delta SENT_{i,t} * (1 - D_{i,t})$ represent the falling trend of investor sentiment at group level.

3.8 The impact of investor sentiment on the relationship between macroeconomic variables and market returns

3.8.1 At the country level, the effect of rising and falling levels of investor sentiment on the relationship between macroeconomic variables and equity returns is measured using the following equation:

$$R_t = \beta_0 + \beta_1 SENT_t^* + \beta_2 IPI_t + \beta_3 TBill_t + \beta_4 TS_t + \tag{22}$$
$$\beta_5 SENT_t^* * \Delta SENT_t * D_t + \beta_6 IPI_t * \Delta SENT_t * D_t + \beta_7 TBill_t * \Delta SENT_t * D_t +$$
$$\beta_8 TS_t * \Delta SENT_t * D_t + \beta_9 \; \Delta SENT_t * (1 - D_t) + \beta_{10} IPI_t * \; \Delta SENT_t * (1 - D_t) +$$
$$\beta_{11} TBill_t * \; \Delta SENT_t * (1 - D_t) + \beta_{12} TS_t * \; \Delta SENT_t * (1 - D_t) + \beta_{13} AR_{t-1} + \; \varepsilon_t$$

Where $SENT_t^*$ represents investor sentiment for each country, $TBill_t$ represents the risk-free rate of the selected specific country, IPI_trepresents Industrial Production Index for each country and TS_t represents Term Spread for each country. The interactions terms $(\beta_6 IPI_t * \Delta SENT_t * D_t, \; \beta_7 TBill_t * \Delta SENT_t * D_t, \beta_8 TS_t * \Delta SENT_t * D_t)$ represents the effect with the rising trend of investor sentiment, $(SENT_t * (1 - D_t), \beta_{10} IPI_t * \Delta SENT_t * (1 - D_t), \; \beta_{11} TBill_t * \Delta SENT_t * (1 - D_t), \; \beta_{12} TS_t * \Delta SENT_t * (1 - D_t)$ represents effect with falling trends of investor sentiment.

3.8.2 At the group level, the effect of rising and falling levels of investor sentiment on the relationship between the macroeconomic variable and equity returns is measured using the following equation:

$$R_{i,t} \;=\; \beta_0 + \; \beta_1 SENT_{i,t}^* \; + \beta_2 IPI_{i,t} + \beta_3 TBill_{i,t} + \beta_4 TS_{i,t} + \; \beta_5 SENT_{i,t}^* \tag{23}$$

$$*\varDelta SENT_{i,t} * D_{i,t} + \beta_6 IPI_{i,t} * \varDelta SENT_{i,t} * D_{i,t} + \beta_7 TBill_{i,t} * \varDelta SENT_{i,t} * D_{i,t} +$$

$$\beta_8 TS_{i,t} * \varDelta SENT_{i,t} * D_{i,t} + \beta_9 \varDelta SENT_{i,t} * (1 - D_{i,t}) + \beta_{10} IPI_{\boldsymbol{i,t}} *$$

$$\varDelta SENT_{i,t} * (1 - D_{i,t}) + \beta_{11} TBill_{\boldsymbol{i,t}} * \ \varDelta SENT_{i,t} * (1 - D_{i,t}) + \beta_{12} TS_{\boldsymbol{i,t}} *$$

$$\varDelta SENT_{i,t} * (1 - D_{i,t}) + \beta_{13} AR_{i,t-1} + \quad \varepsilon_{i,t}$$

Where $SENT^*_{i,t}$ represents investor sentiment for the group level, $TBill_{i,t}$ represents the risk-free rate of selected group level, $IPI_{i,t}$represents Industrial Production Index for group level and $TS_{i,t}$ represents Term Spread for group level. The

interactions terms ($\beta_6 IPI_{i,t} * \varDelta SENT_{i,t} * D_t$, $\beta_7 TBill_{i,t} * \varDelta SENT_{i,t} * D_t, \beta_8 TS_{i,t} * \varDelta SENT_{i,t} * D_t$) represents the effect with the rising trend of investor sentiment, $(SENT_{i,t} * (1 - D_t)\,, \beta_{10} IPI_{i,t} * \ \varDelta SENT_{i,t} * (1 - D_{i,t})\,,\ \beta_{11} TBill_{i,t} * \ \varDelta SENT_{i,t} * (1 - D_{i,t})\,,\ \beta_{12} TS_{i,t} * \ \varDelta SENT_{i,t} * (1 - D_{i,t}))$ represents effect with falling trends of investor sentiment.

3.9 Impact of COVID-19 on the Relationship between Investor Sentiment and Equity Market Returns

3.9.1 At the country level, the following equation is used;

$$R_t \ = \ \beta_0 + \ \beta_1 \ SENT_t + \beta_2 COVID_t + \tag{24}$$

$$\beta_3 SENT_t * COVID_t + \beta_4 AR_{t-1} + \varepsilon_t$$

Where R_t is the return, $SENT_t$ is the investor sentiment, and $(SENT_t * COVID_t)$ is the interaction term of investor sentiment with COVID-19.

3.9.2 At the group level, the following equation is used;

$$R_{i,t} = \beta_0 + \beta_1 SENT_{i,t} + \beta_2 COVID_{i,t} + \beta_3 SENT_{i,t} * COVID_{i,t} + \beta_4 AR_{i,t-1} + \varepsilon_{i,t} \quad (25)$$

Where $R_{i,t}$ is the return, $SENT_{i,t}$ is the investor sentiment, $(SENT_{i,t} * COVID_{i,t})$ is the interaction term of investor sentiment with COVID-19.

Chapter 4

Results and Discussion

This chapter presents descriptive statistics for illustration of the data, derivation of results, and discussions on the main findings of the study.

4.1 Descriptive Statistics

Table 4.1 reports the descriptive statistics of the variables studied, i.e., market returns, sentiment, Δ sentiment, T-bills, term Spread, industrial production index, market premiums, VaR-95, VaR-99, CVaR-95, and CVaR-99 for country and group level.

Table 4.1 shows 5218 observations for each of the seven countries in the sample. RTP is market index returns, SENTIM is sentiment index, ΔSENTIMENT is changed in sentiment index, TS is term spread, TB is the risk-free rate, IPI is industrial production index, RP is risk premium, VaR-95 is Value at Risk at 95% confidence interval, VaR-99 is Value at Risk at 99% confidence interval, CVaR-95 is Conditional Value at Risk at 95% confidence interval, and CVaR-99 is Conditional Value at Risk at 99% confidence interval.

Daily stock returns are positive for all sample countries, with the lowest average returns (0.0275%) for South Africa and the highest average returns (0.0758%)for Pakistan. The maximum variability of returns (9.4379% to -9.8725%) is observed in Russia, and the minimum variability (7.6234% to -9.2997%) is observed in Indonesia.

Table 4.1: Descriptive Statistics

	Brazil	**Russia**	**Indonesia**	**India**	**China**	**South Africa**	**Pakistan**	**Panel**
				RETURNS (RTP)				
Mean	0.0566	0.0434	0.0498	0.0586	0.0395	0.0275	0.0758	0.0498
Median	0.1019	0.1253	0.1117	0.0981	0.0779	0.0640	0.1053	0.0969
Maximum	9.2475	9.4379	7.6234	7.9691	9.4008	9.0570	8.2547	9.6186
Minimum	-9.8312	-9.8725	-9.2997	-9.1046	-9.2562	-8.3828	-7.7414	-9.8725
Std. Dev.	1.7352	1.9436	1.2953	1.3722	1.5067	1.3126	1.2922	1.5149
Skewness	-0.2692	-0.4314	-0.7708	-0.4395	-0.3624	-0.0805	-0.4917	-0.4180
Kurtosis	6.7135	7.5637	9.7846	8.0607	8.1124	7.5924	6.4138	8.5575
				SENTIMENT (SENTIM)				
Mean	-0.0002	-0.0007	0.0000	0.0146	0.0000	0.0000	-0.0183	-0.0004
Median	-0.7583	0.3182	0.0004	-0.1631	0.0461	0.1169	-0.1954	-0.0757
Maximum	5.8453	6.5330	7.6657	5.6438	5.9152	9.5081	7.4606	9.5081
Minimum	-1.3048	-2.4861	-4.6454	-5.3668	-2.8464	-3.5152	-5.9747	-5.9747
Std. Dev.	1.3516	1.3613	1.3492	1.3947	1.3439	1.3042	1.3310	1.3482
Skewness	1.3920	0.3030	0.7548	1.1240	0.5384	-0.5610	0.4055	0.5901
Kurtosis	4.6646	2.3486	5.1726	4.7595	3.7478	7.5907	6.8124	4.9479
				ΔSENTIMENT (ΔSENTIM)				
Mean	-0.0004	0.0007	0.0014	0.0007	0.0008	0.0006	0.0000	0.0006
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	7.0644	4.2780	5.0288	8.4438	2.0867	10.1657	4.6592	10.1657

Minimum	-7.1005	-2.8093	-5.2177	-6.0027	-1.7985	-10.0138	-4.3536	-10.0138
Std. Dev.	0.8229	0.3937	0.4926	0.5044	0.2642	0.7405	0.5097	0.5614
Skewness	-0.0110	0.7818	0.1173	0.6824	0.3743	0.0947	-0.0077	0.1501
Kurtosis	47.6525	14.7048	17.9595	33.7824	8.8700	36.2764	8.5240	53.1326
T-Bills (TB)								
Mean	12.2807	8.5142	8.2104	6.6705	1.0321	7.4251	8.5154	7.5096
Median	11.7515	7.6555	7.1804	6.0000	0.3000	7.1150	8.8100	7.0300
Maximum	28.78	27.8300	17.3900	10.2500	4.7600	12.7400	14.0100	28.7800
Minimum	2.0036	4.2000	4.0600	4.2500	0.0100	3.4500	1.2100	0.0100
Std. Dev.	5.138984	3.4536	3.1043	1.2264	1.2580	2.0240	3.3123	4.3909
Skewness	0.304976	1.8821	1.3162	0.9567	1.2404	0.7401	-0.2633	0.7107
Kurtosis	3.046224	8.6764	4.0252	3.4356	3.2989	3.0792	2.3962	4.5019
TERM SPREAD (TS)								
Mean	-0.2203	0.8143	1.4614	0.7S909	1.0286	0.5209	-0.0100	0.6272
Median	0.1660	0.9500	1.1995	0.6240	0.9400	1.1500	-0.0097	0.7130
Maximum	5.7500	7.1120	6.5880	3.2320	3.9500	5.1350	0.1249	7.1120
Minimum	-25.0575	-7.3900	-4.2760	-1.8970	-0.8380	-11.6200	-0.1300	-25.0575
Std. Dev.	3.6521	2.4841	0.9726	0.7780	0.4262	2.3359	0.0333	2.0255
Skewness	-5.3347	-1.2450	0.8187	0.8566	1.0522	-2.2496	0.6080	-5.7652
Kurtosis	35.4485	6.0778	3.4766	3.7975	4.4071	10.2449	10.9703	66.0694
INDUSTRIAL PRODUCTION INDEX (IPI)								
Mean	97.0220	134.5883	104.2800	81.8216	97.8604	111.2959	97.0220	103.4117

Median	99.9027	137.7056	97.9985	80.9702	98.0083	111.5000	99.9027	102.0304
Maximum	135.5511	181.4030	149.0540	123.4824	125.1021	135.1089	135.5511	181.4030
Minimum	36.0068	83.3553	55.0730	3.4697	79.7375	92.9173	36.0068	3.4697
Std. Dev.	16.9459	24.3976	16.6906	18.2289	5.3321	6.0488	16.9459	22.2400
Skewness	-0.4430	-0.1415	0.4735	-0.6246	0.4429	0.2744	-0.4430	0.4732
Kurtosis	2.4819	2.1370	2.5857	4.4048	3.4468	3.4006	2.4819	4.5546
RISK PREMIUM (RP)								
Mean	0.0003	0.0001	0.0003	0.0004	0.0004	0.0001	0.0005	0.000281
Median	0.0007	0.0011	0.0009	0.0008	0.0008	0.0005	0.0008	0.000767
Maximum	0.1367	0.1637	0.0732	0.0795	0.0902	0.0904	0.0822	0.201774
Minimum	-0.1302	-0.2121	-0.1097	-0.1392	-0.0887	-0.1047	-0.0776	-0.21247
Std. Dev.	0.0176	0.0201	0.0129	0.0138	0.0149	0.0132	0.0129	0.015429
Skewness	-0.1384	-0.7804	-0.9728	-0.6614	-0.3754	-0.1300	-0.4916	-0.5286
Kurtosis	8.2274	12.7519	11.4568	10.2230	7.7746	7.9706	6.4066	13.05416
Value at Risk at 95% (VaR-95)								
Mean	-0.0229	-0.0242	-0.0159	-0.0166	-0.0192	-0.0167	-0.0153	-0.0187
Median	-0.0197	-0.0201	-0.0132	-0.0134	-0.0160	-0.0143	-0.0122	-0.0155
Maximum	-0.0016	-0.0011	-0.0016	0.0002	-0.0015	-0.0013	0.0009	0.0009
Minimum	-0.1489	-0.1472	-0.0712	-0.0863	-0.0882	-0.0833	-0.0671	-0.1489
Std. Dev.	0.0147	0.0171	0.0104	0.0121	0.0129	0.0102	0.0110	0.0133
Skewness	-3.9542	-2.7435	-1.8982	-2.5097	-1.8647	-2.6504	-1.3873	-2.8120
Kurtosis	28.6803	14.7234	7.6428	11.4905	7.2387	14.8282	5.0272	17.9598

Value at Risk at 99% (VaR-99)								
Mean	-0.0297	-0.0326	-0.0219	-0.0223	-0.0264	-0.0212	-0.0202	-0.0253
Median	-0.0261	-0.0264	-0.0180	-0.0179	-0.0216	-0.0183	-0.0178	-0.0213
Maximum	-0.0038	-0.0029	-0.0028	-0.0024	-0.0033	-0.0030	-0.0001	-0.0001
Minimum	-0.1578	-0.1984	-0.1016	-0.1280	-0.0887	-0.1002	-0.0706	-0.1977
Std. Dev.	0.0174	0.0233	0.0142	0.0168	0.0162	0.0123	0.0125	0.0172
Skewness	-3.1652	-2.7966	-2.0036	-3.2442	-1.4469	-2.3664	-1.0592	-2.7661
Kurtosis	19.1417	15.0549	8.3995	17.6735	4.8743	12.6425	4.2655	16.8588
Conditional Value at Risk at 95% (CVaR-95)								
Mean	-0.0275	-0.0298	-0.0198	-0.0204	-0.0239	-0.0198	-0.0186	-0.0230
Median	-0.0239	-0.0247	-0.0170	-0.0160	-0.0197	-0.0170	-0.0157	-0.0192
Maximum	-0.0030	-0.0028	-0.0026	-0.0018	-0.0027	-0.0026	-0.0001	-0.0001
Minimum	-0.1549	-0.2120	-0.0905	-0.1129	-0.0887	-0.0942	-0.0774	-0.2120
Std. Dev.	0.0163	0.0212	0.0126	0.0150	0.0147	0.0116	0.0120	0.0156
Skewness	-3.4249	-3.0096	-1.8565	-2.9990	-1.5625	-2.4135	-1.3446	-2.8644
Kurtosis	22.2700	17.8926	7.2739	15.4824	5.5441	12.9049	5.6251	18.7650
Conditional Value at Risk at 99% (CVaR-99)								
Mean	-0.0315	-0.0347	-0.0234	-0.0238	-0.0282	-0.0224	-0.0215	-0.0270
Median	-0.0272	-0.0284	-0.0193	-0.0192	-0.0229	-0.0190	-0.0188	-0.0226
Maximum	-0.0044	-0.0030	-0.0030	-0.0028	-0.0036	-0.0032	-0.0001	-0.0001
Minimum	-0.1599	-0.2120	-0.1095	-0.1390	-0.0926	-0.1045	-0.0774	-0.2120
Std. Dev.	0.0185	0.0255	0.0155	0.0183	0.0176	0.0130	0.0132	0.0186

Skewness	-2.9550	-2.8262	-2.1497	-3.3531	-1.4340	-2.2837	-1.0220	-2.7919
Kurtosis	16.7624	15.0711	9.6678	18.6567	4.7911	11.9226	4.2339	16.8799
Observations	5218	5218	5218	5218	5218	5218	5218	36533

SENTIM is the sentiment index, ΔSENTIMENT is the change in sentiment index, TS is term spread, TB is the Treasury bill rate, IPI is Industrial Production Index, RP is risk premium, VaR is Value at risk at 95% and 99% confidence interval, CVaR is Value at risk at 95% and 99% confidence interval.

Russia has the highest standard deviation value (1.9436%), while Indonesia has the lowest value (1.2953%). All skewness values are negatively skewed, indicating their presence at the left tail. The kurtosis values are greater than three, meaning the data is not normal.

Regarding the investor sentiment index, the mean values are positive for Indonesia, India, China, and South Africa, whereas, negative for Brazil, Russia, and Pakistan i.e., investor sentiment is positive in most sample countries. The standard deviation of the sentiment index is highest (1.3947) in India and lowest (1.3042) in South Africa. The investor sentiment index is negatively skewed only for South Africa. The kurtosis values in most of the selected countries are greater than three but not excessively high. The skewness and kurtosis of the sentiment index show that the data is not normal. Because of this, Δsentiment is used to improve statistical inference. The mean values of Δsentim are positive for all the countries except Brazil. The standard deviation of Δsentim is highest in Brazil (0.8229) and lowest in China (0.2642). The Δsentim is negatively skewed for Brazil and Pakistan, and kurtosis is more than 3 and is excessively high.

The mean values of T-bills for all the selected countries are positive. The standard deviation of T-Bills is highest (5.1389%) in Brazil and lowest (1.2264%) in India. T-Bills are negatively skewed only for Pakistan while positively skewed for all other countries, and kurtosis is almost 3, indicating normality. The average values of the Industrial Production Index are also positive for all the countries. The values of standard deviation range from (5.3321 to 24.3976) for all the countries showing more variability in the series. The average values of Term Spread are positive for Russia, Indonesia, India, China, South Africa, and Panel, while negative for Brazil and Pakistan. The standard deviation of Term Spread is highest (3.6521) in Brazil and lowest (0.0333) in Pakistan. Term Spread is negatively skewed for Brazil, Russia, South Africa, and Panel while positively skewed for all other countries. Kurtosis is too high in a few cases indicating that Term Spread is highly fat-tailed. The average values of the market premiums are also positive for all countries. The standard deviation values range from (0.0129 to 0.0201) for all countries showing less variability in the series. The market premium is negatively skewed for all countries, and the kurtosis is greater than 3.

The mean values of VaR at 95% range from -0.0242 to -0.0153 across all countries. The standard deviation ranges from 0.0102 to 0.0171; a minimum standard deviation is observed in South Africa (0.0102) and a maximum in Russia (0.0171). The skewness values range from -3.9542 to -1.3873, with negative values indicating a left-skewed distribution. The kurtosis values range from 5.0272 to 28.6803; values above 3 indicate more peaked than a normal distribution. The average values of VaR at 99% range from -0.0326 to -0.0202 across all countries.

The standard deviation ranges from 0.0123 to 0.0233; the minimum standard deviation is observed in South Africa (0.0123) and the maximum in Russia (0.0233). The skewness values range from -3.2442 to -1.0592, negative values indicating a left-skewed distribution. The kurtosis values range from 4.2655 to 19.1417; values above 3 indicate a more peaked distribution than a normal distribution.

The mean values of CVaR at 95% range from -0.0298 to -0.0186. The minimum standard is observed in South Africa (0.0116) and the maximum in Russia (0.0212). The skewness values ranged from -3.4249 to -1.3446. The kurtosis values ranged from 5.5441 to 22.2700; most values are above than 3. The values of CVaR at 99% range from -0.0347 to -0.0215. The minimum standard deviation is observed in South Africa (0.0130) and the maximum in Russia (0.0255). The skewness values ranged from -3.3531 to -1.0220. The kurtosis values ranged from 4.2339 to 18.6567.

4.2 Investor Sentiment and Contemporaneous Market Returns

Table 4.2 reports the impact of investor sentiments and macroeconomic variables on contemporaneous returns of the sample equity markets.

TABLE 4.2: Impact of Investor Sentiment on Contemporaneous Market Returns

Investor Sentiment and Contemporaneous Returns – Brazil				
Variable	**Coefficient**	**Std. Error**	**T-statistic**	**Prob.**
CONSTANT	-0.464805	0.498158	-0.933048	0.3509
SENTIM	0.204895	0.110161	1.859955	0.0631

$SENTIM^2$	-0.045126	0.025055	-1.801081	0.0719
TS	0.000861	0.008006	0.107528	0.9144
TB	-0.007968	0.010490	-0.759547	0.4476
IPI	0.004764	0.004363	1.091976	0.2750
AR(1)	0.085782	0.022841	3.755580	0.0002
Adj. R^2	0.001058			
D. Watson	1.945646			
Investor Sentiment and Contemporaneous Returns– Russia				
CONSTANT	1.579540	0.508324	3.107350	0.0019
SENTIM	0.073643	0.055426	1.328662	0.104
$SENTIM^2$	-0.067299	0.010687	-6.297382	0.0000
TS	-0.044433	0.028126	-1.579804	0.1142
TB	-0.032430	0.016461	-1.970162	0.0489
IPI	-0.007840	0.003892	-2.014478	0.0440
AR(1)	-0.764479	0.078533	-9.734561	0.0000
Adj. R^2	0.030681			
D. Watson	1.999769			
Investor Sentiment and Contemporaneous Returns – Indonesia				
CONSTANT	0.806359	0.350559	2.300207	0.0215
SENTIM	0.183050	0.028498	6.423344	0.0000
$SENTIM^2$	-0.011975	0.007686	-1.557952	0.1093
TB	0.028715	0.014714	1.951568	0.0510
TS	0.023118	0.029642	0.779899	0.4355
IPI	-0.009357	0.002630	-3.557235	0.0004
AR(1)	-0.495966	0.049420	-10.03580	0.0000
Adj. R^2	0.045669			
D. Watson	1.999945			
Investor Sentiment and Contemporaneous Returns – India				
CONSTANT	0.471007	0.221023	2.131034	0.0331
SENTIM	-0.045581	0.016875	-2.701072	0.0069
$SENTIM^2$	0.002939	0.004191	0.701257	0.4832
TS	-0.000690	0.000489	-1.411501	0.1582
TB	-0.021977	0.024620	-0.892653	0.3721
IPI	-0.003343	0.001525	-2.192671	0.0284
AR(1)	0.130393	0.006567	19.85578	0.0000
Adj. R^2	0.017057			
D. Watson	2.003279			
Investor Sentiment and Contemporaneous Returns – China				

CONSTANT	-4.266229	1.034888	-4.122406	0.0000
SENTIM	0.384214	0.043589	8.814439	0.0000
SENTIM∧2	-0.060503	0.009964	-6.072348	0.0000
TS	0.242169	0.080028	3.026057	0.0025
TB	0.187816	0.039389	4.768210	0.0000
IPI	0.041013	0.010493	3.908641	0.0001
AR(1)	-0.895273	0.071470	-12.52662	0.0000
Adj. R^2	0.020679			
D. Watson	1.999085			
Investor Sentiment and Contemporaneous Returns – South Africa				
CONSTANT	-0.154717	0.468257	-0.330410	0.7411
SENTIM	-0.040018	0.019200	-2.084314	0.0372
SENTIM∧2	0.003665	0.004127	0.888119	0.3745
TB	-0.046354	0.014339	-3.232687	0.0012
TS	-0.004849	0.009069	-0.534631	0.5929
IPI	0.004767	0.004426	1.076949	0.2816
AR(1)	-0.358148	0.106428	-3.365158	0.0008
Adj. R^2	0.011657			
D. Watson	1.997589			
Investor Sentiment and Contemporaneous Returns – Pakistan				
CONSTANT	0.343593	0.261824	1.312306	0.1895
SENTIM	0.386019	0.028837	13.38643	0.0000
SENTIM∧2	0.028399	0.006759	4.201521	0.0000
TB	0.036436	0.013591	2.680959	0.0074
TS	2.016163	0.833594	2.418638	0.0156
IPI	-0.005553	0.002381	-2.332382	0.0197
AR(1)	-0.659972	0.044931	-14.68841	0.0000
Adj. R^2	0.084233			
D. Watson	1.996081			
Panel Data Analysis				
CONSTANT	0.160914	0.040910	3.933323	0.0001
SENTIM	0.026633	0.007570	3.518096	0.0004
SENTIM∧2	-0.000933	0.003368	-0.277141	0.7817
TB	-0.000728	0.002344	-0.310641	0.7561
TS	-0.004655	0.004392	-1.059791	0.2892
IPI	-0.001042	0.000354	-2.945576	0.0032
AR(1)	0.115118	0.013553	8.493618	0.0000
Adj. R^2	0.014006			

D. Watson	2.005229

SENTIM is the sentiment index, SENTIM∧2 is a nonlinear term, TS is the term spread, TB is the Treasury bill rate, and IPI is Industrial Production Index. AR is Auto Regressive term.

The investor sentiments have a significant positive impact on same-day returns of Brazil, Russia, Indonesia, China, and Pakistan equity markets.

The impact is linear in India and South Africa and non-linear in other markets.

The negative sign of the quadratic term underscores the convexity of the relationship. Brown and Cliff (2004) observe the negative influence, suggesting misprices in the equity market are corrected at a further higher level.

Investor sentiments significantly negatively impact the returns of equity markets of India and South Africa. The impact is only linear in these markets and highlights that rising sentiments reduce returns.

It is further evident from Table 4.2 that at the panel data level, investor sentiment has a significant positive impact on contemporaneous market returns in a linear fashion.

The positive influence is supported by the studies of Hu et al. (2013) and Lux (2012), indicating that a higher level of investor sentiments leads to higher returns.

The nonlinear term is found insignificant in India and group level and lines up with the study of Bekiros et al. (2016).

4.3 Investor Sentiment and Future Equity Returns

Table 4.3 reports the link between investor sentiment and returns after a period of 1 day, 5 days, 10 days, 20 days, 40 days, 60 days,180 days, and 240 days.

A time period of less than one month is considered a short time horizon, whereas time from one month to one year is taken as a long horizon.

TABLE 4.3: Investor Sentiment and Market Returns at different time horizons

Investor Sentiments and Market Returns -Brazil								
	Short horizon				**Long horizon**			
hline **Variable**	$\mathbf{R}_{t+1}$	$\mathbf{R}_{t+5}$	$\mathbf{R}_{t+10}$	$\mathbf{R}_{t+20}$	$\mathbf{R}_{t+40}$	$\mathbf{R}_{t+60}$	$\mathbf{R}_{t+180}$	$\mathbf{R}_{t+240}$
CONSTANT	-0.622754***	0.836602*	0.088666	0.049209	0.115650	0.125437	0.225402	0.178840
SENTIM	-0.160632***	-0.126118*	0.020531	0.007539	0.024972	0.054753*	0.036798	0.063976*
SENTIM2	0.046177*	0.039777***	-0.009822	-0.010535	-0.024734***	-0.023425***	-0.002876	-0.002743
TS	0.013610	-0.003549	-0.008674	-0.012428*	-0.011613*	-0.007072	-0.013444*	-0.004321
TB	-0.01081	0.005403	0.003297	0.007628	0.005727	-0.002296	-0.000826	-0.009477*
IPI	0.006831***	-0.007277*	-0.000614	-0.000758	-0.000913	5.70E-07	-0.001569	3.86E-05
Adj R2	0.028	0.005	0.001	0.002	0.003	0.002	0.002	0.002
D-W	2.444781	1.713432	1.970089	1.971209	1.971879	1.970856	1.969798	1.9794
Investor Sentiments and Market Returns -Russia								
CONSTANT	0.123382	0.156853**	0.034118	-0.018271	-0.115994*	-0.075221	0.025015	-0.059309
SENTIM	-0.109287***	-0.053387**	-0.059444***	-0.046821*	-0.047267*	-0.045154*	0.039018*	-0.047310*
SENTIM2	0.037697***	0.010693	0.044779***	0.014699	0.033754**	0.013587	0.018137	0.045949***
TS	-0.046263***	-0.022339*	-0.009753	-0.001745	-0.002160	-0.003755	0.013803	-0.005905
TB	-0.035588***	-0.014053**	-0.008367	0.003202	0.010744*	0.010102	0.003311	0.001089
Adj R2	0.029	0.026	0.029	0.024	0.027	0.026	0.0005	0.027
D-W	1.998700	1.997695	2.001632	1.993152	1.993585	1.994249	1.683372	1.999413
Investor Sentiments and Market Returns -Indonesia								
CONSTANT	0.336155*	0.382218*	0.374791*	0.256437	0.177479	0.224008	0.259363	0.232205

SENTIM	0.039387*	0.002615	0.017445	0.001556	0.023771	0.012577	0.045686*	0.002998
SENTIM2	0.004670	0.006173	0.004868	0.002646	0.013427*	0.012061*	0.000332	0.002347
TB	0.004370	0.008506	0.000586	0.003373	0.006730	0.003898	0.004820	0.005883
TS	0.019758	0.004998	0.020842	0.000150	0.007587	0.016960	0.011712	0.008871
IPI	0.003330**	0.002573*	0.003461**	0.001778	0.001042	0.001319	0.002390	0.002159
AR (1)	0.068378***	0.192371***	0.192163***	0.193236***	0.193593***	0.191329***	0.191411***	0.191706***
Adj R2	0.005	0.039	0.04	0.039	0.04	0.039	0.039	0.039
D-W	1.630171	1.999372	1.999293	1.999376	1.999462	1.999189	1.999477	1.999201
Investor Sentiments and Market Returns -India								
CONSTANT	-0.027315	0.840594***	0.771072***	-0.390756	0.684602***	-0.619058*	-0.240051	0.348827
SENTIM	0.120486	0.002449	-0.014381	-0.194701**	0.007064	0.009996	-0.022582	0.152472*
SENTIM2	-0.047557***	-0.014173***	-0.010995*	0.048211***	-0.017120***	0.005501	0.026514*	-0.023695*
TS	0.182740***	0.041560*	0.037281*	0.149576***	0.037240*	0.148187***	0.029843	-0.064365*
TB	0.090757*	-0.084872***	-0.069666**	0.130871***	-0.057485*	0.099141**	0.025055	-0.069139*
IPI	-0.009367***	-0.002831*	-0.003201**	-0.005730***	-0.002818**	-0.002062	0.000785	0.001319
Adj R2	0.036	0.012	0.002	0.012	0.003	0.006	0.009	0.004
D-W	1.972589	1.759697	1.769311	1.986917	1.762261	1.685769	2.007870	1.961537
Investor Sentiments and Market Returns -China								
CONSTANT	-0.508671	-0.376836	-0.363796	0.179582	-0.073682	0.226249	-0.034639	0.278439
SENTIM	0.047760***	0.043803**	0.047542*	0.028908	0.043946*	0.036207*	0.006713	-0.012840
SENTIM2	-0.015853***	-0.021475***	-0.023926***	0.030439***	-0.023667***	-0.017203**	-0.014437**	-0.006155
TS	0.005504	0.037341	0.043194	0.000770	0.103496*	0.110351*	0.022410	-0.008325

TB	0.052880***	0.066213***	0.069134***	0.063533***	0.059709***	0.058943***	0.037110**	0.028810*
IPI	0.005200	0.003560	0.003389	0.001538	-0.000140	-0.003400	0.000387	-0.002544
AR(1)	0.192490***	0.036401***	0.782514***	0.788380***	0.785593***	0.787428***	0.064021***	0.805747***
Adj R2	0.013	0.008	0.01	0.01	0.0009	0.009	0.004	0.008
D-W	1.991523	1.997833	1.993697	1.992977	1.993637	1.992974	2.001834	1.996693
Investor Sentiments and Market Returns –South Africa								
CONSTANT	0.236933	-0.780548*	0.176787	0.277281	0.453814*	0.551859*	0.159813	0.037277
ΔSENTIM	0.023511	0.033998	0.013561	0.008067	-0.034448*	-0.023424	-0.022972	0.018434
ΔSENTIM2	0.014483**	0.014252**	-0.000399	0.003136	0.001589	0.004430	0.014973*	0.005696
TS	-0.001457	0.020484	-0.005311	0.000890	-0.008970	-0.003536	0.010368*	-0.001326
TB	-0.026160***	-0.005404	-0.028066***	-0.029300***	-0.028821***	-0.024238***	-0.009205	-0.007899
IPI	-0.000213	0.007234*	0.000553	-0.000320	-0.001886	-0.003102	-0.000666	0.000437
AR(1)	0.052525***	-0.102042***	-0.017743**	-0.020531**	0.996514***	0.996338***	0.988283***	1.001840***
Adj R2	0.011	0.016	0.011	0.012	0.012	0.011	0.011	0.099
D-W	1.997595	1.859148	1.999737	1.987652	1.990963	1.988252	1.982433	1.988703
Investor Sentiments and Market Returns -Pakistan								
CONSTANT	0.199576*	0.193348	0.227494*	0.190085*	0.196475	0.136581	0.118795	0.118004
SENTIM	0.042032***	0.044933***	0.053462***	0.008476	0.022258*	0.009693	0.009644	0.010524
SENTIM2	0.000723	0.009208**	0.018769***	0.023798***	0.005893*	0.007207**	0.007677	0.009162*
TS	0.892403*	0.027055	0.659842	1.586349***	0.012867	0.241910	0.940325*	0.251002
TB	0.007754	0.007918	0.003660	0.010133*	0.006968	0.007208	0.006993	0.001771
IPI	0.000609	0.000336	0.000946	5.32E-07	0.000505	0.000192	0.000170	0.000645

AR(1)	0.075068***	0.179942***	0.178467***	0.186288***	0.562588***	0.564061***	0.571824***	0.974568***
Adj R2	0.013	0.043	0.045	0.042	0.042	0.042	0.042	0.039
D-W	1.659891	2.001380	2.001351	2.019094	1.988736	1.988028	1.987092	2.001152
Panel Data Analysis								
SENTIM	0.012355**	0.014042**	0.015073**	0.011687*	0.005208	0.001180	0.002248	0.000768
SENTIM2	0.001407	0.000780	0.004997**	0.007247***	0.005145*	0.002521	0.003087	0.003298
TS	0.003714	0.001862	0.001944	0.001452	0.005265	0.003503	0.003680	0.005784
TB	0.001329	0.000560	0.000200	0.000940	0.001048	0.001420	0.002092	0.002243
IPI	0.000937***	0.001130***	0.001317***	0.001247***	0.001179***	0.000951**	0.000802*	0.000918*
AR(1)	0.125315***	0.032914***	0.017994***	0.123187***	0.120573***	0.120301***	0.118475***	0.118270***
Adj R2	0.016	0.017	0.016	0.015	0.016	0.016	0.015	0.015
D-W	1.999943	2.000565	2.000314	2.007224	1.999944	2.000475	1.998940	2.000310

SENTIM is the sentiment index, TS is term spread, TB is the Treasury bill rate, and IPI is Industrial Production Index. AR is Auto Regressive term. * is significant at 1%. ** is significant at 5% and *** denotes significance at 10%. Adj R2 is in % term.

Table 4.3 reveals that investor sentiment predicts the market returns after 1 day and 5 days in Brazil. This relationship is negative and nonlinear. At a longer time frame, the link is significant and positive at 60 and 240 days. This indicates that the market observes a reduction in return with increased sentiments exhibited through volume, which may be selling pressure in this case but reverses subsequently. The relationship is nonlinear on days 1, 5, 40, and 60. This reversal implies that deviation in the prices from their fundamental value observed in the short term is converged towards its fundament value in the long term, both in the linear and nonlinear term. The negative link is aligned with the study of Da et al. (2023), and the positive follows the results of Cheema et al. (2020a) in the short run and linear settings. In the long run, in non-linear settings, the positive link is aligned with Fang et al. (2018), and the negative link is aligned with the study of Baker et al. (2012).

The nonlinear term significantly and positively influences returns after 1 day, 5 days, 10 days, and 40 days. This indicates the convexity of the link between sentiments and market returns. The results follow the study of Cheema et al. (2020a). The influence of sentiments is not much pronounced in the Indonesian equity market. In Indonesia, investor sentiment predicts market returns for the next day only in a linear fashion and returns after 180 days in a nonlinear way. Investor sentiment is observed to be a poor predictor in the short term, as noted by Yelamanchili et al. (2019), and in the long term, as concluded by Kling and Gao (2008).

In the Chinese market, higher investor sentiments result in higher returns on subsequent days, i.e., days 1, 5, 10, 40, and 60. This relationship is convex and nonlinear in nature regarding subsequent returns. It means returns increase at decreasing rate with sentiments. The positive link is aligned with the study of Ruan et al. (2020). The significant nonlinear link between investor sentiments and the subsequent market return is also observed in the Indian and South African markets. Positive results are observed in the study of Kling and Gao (2008) and negative in the study of Ma et al. (2021). The Pakistani market exhibits a significant positive nonlinear link between investor sentiments and subsequent equity returns in the short run, and this relation is also non-linear. The interesting feature is that returns increase at an increasing rate in general.

The dynamic panel data analysis exhibits a linear relationship between investor sentiments and subsequent market returns after days 1 and 5. The relationship is nonlinear for returns after 10, 20, and 60 days. These results are consistent with Ruan et al. (2020) and Fang et al. (2018) in the short and long run. The interest rates and term spread do not impact returns in sample countries and a group. Industrial production has a positive link with market returns, which aligns with the argument that an increase in growth rate is priced by the market and results in higher returns.

It is worth mentioning that interest rate generally has an insignificant impact on the market returns of Brazil, Russia, Indonesia, and Pakistan at several time frames. However, a significant impact is observed on the returns of India and China. The diverse signs may be the different economic models where states have varying degrees of control. However, panel data analysis reveals that no effect is observed at the group level. A similar pattern is seen regarding the influence of term spread. Industrial production has a positive impact on the returns of Brazil and Indonesia, no impact on the returns of China and Pakistan, negative impact on the returns of India.

4.4 Optimistic and Pessimistic Investor Sentiment and Equity Returns

Table 4.4 reports the impact of optimistic and pessimistic investor sentiment on equity market returns in linear and non-linear settings at both country as well as group levels.

TABLE 4.4: Effect of Optimistic and Pessimistic Investor Sentiment on Equity Returns at Country and Group Level

Optimistic and Pessimistic Investor Sentiment and Equity Returns – Brazil				
Variable	**Coefficient**	**Std. Error**	**T-statistic**	**Prob.**
CONSTANT	0.0282	0.0490	0.5750	0.5653
ΔSENTM $*D_1$	0.2346	0.1139	2.0599	0.0395
ΔSENTIM $*D_2$	0.3881	0.1521	2.5511	0.0108
ΔSENTIM^2 $*D_1$	-0.0477	0.0212	-2.2517	0.0244

$\Delta SENTIM^2 *D_2$	0.0662	0.0252	2.6262	0.0087
RP	-0.0021	0.0039	-0.5368	0.5914
AR(1)	0.3397	0.0267	12.6997	0.0000
Adj. R^2	0.0025			
D. Watson	2.0001			
Optimistic and Pessimistic Investor Sentiment and Equity Returns – Russia				
CONSTANT	0.2566	0.1234	2.0796	0.0376
$\Delta SENTM *D_1$	0.3825	0.0989	3.8689	0.0001
$\Delta SENTIM *D_2$	-0.0295	0.0846	-0.3491	0.7270
$\Delta SENTIM^2 *D_1$	0.2365	0.0840	2.8156	0.0049
$\Delta SENTIM^2 *D_2$	-0.1612	0.0285	-5.6480	0.0000
RP	0.0206	0.0105	1.9547	0.0507
AR(1)	-0.5091	0.0657	-7.7453	0.0000
Adj. R^2	0.0311			
D. Watson	1.9967			
Optimistic and Pessimistic Investor Sentiment and Equity Returns – Indonesia				
CONSTANT	0.0238	0.0297	0.8004	0.4235
$\Delta SENTM *D_1$	0.5234	0.0803	6.5171	0.0000
$\Delta SENTIM *D_2$	0.4929	0.0890	5.5365	0.0000
$\Delta SENTIM^2 *D_1$	-0.1761	0.0373	-4.7242	0.0000
$\Delta SENTIM^2 *D_2$	0.1331	0.0406	3.2807	0.0010
RP	0.0007	0.0026	0.2562	0.7978
AR(1)	0.5480	0.0833	6.5827	0.0000
Adj. R^2	0.0530			
D. Watson	2.0003			
Optimistic and Pessimistic Investor Sentiment and Equity Returns – India				
CONSTANT	0.1333	0.1202	1.1090	0.2675
$\Delta SENTM *D_1$	-0.0394	0.0830	-0.4752	0.6346
$\Delta SENTIM *D_2$	0.2082	0.0815	2.5534	0.0107
$\Delta SENTIM^2 *D_1$	-0.0221	0.0289	-0.7676	0.4428
$\Delta SENTIM^2 *D_2$	0.2121	0.0147	14.3930	0.0000
RP	0.0108	0.0184	0.5851	0.5585
AR(1)	0.1895	0.0299	6.3288	0.0000
Adj. R^2	0.0256			
D. Watson	2.0001			
Optimistic and Pessimistic Investor Sentiment and Equity Returns – China				
CONSTANT	-0.1254	0.0276	-4.5454	0.0000
$\Delta SENTM *D_1$	1.9448	0.1580	12.3082	0.0000

ΔSENTIM $*D_2$	0.6282	0.2041	3.0783	0.0021
ΔSENTIM^2 $*D_1$	-0.4299	0.1446	-2.9734	0.0030
ΔSENTIM^2 $*D_2$	0.1220	0.1644	0.7419	0.4582
RP	-0.0367	0.0086	-4.2553	0.0000
AR(1)	0.5838	0.0353	16.5287	0.0000
Adj. R^2	0.0563			
D. Watson	2.0040			
Optimistic and Pessimistic Investor Sentiment and Equity Returns – South Africa				
CONSTANT	-0.0605	0.0541	-1.1174	0.2639
ΔSENTM $*D_1$	0.2290	0.1234	1.8560	0.0636
ΔSENTIM $*D_2$	0.2035	0.0959	2.1225	0.0339
ΔSENTIM^2 $*D_1$	-0.0568	0.0264	-2.1494	0.0317
ΔSENTIM^2 $*D_2$	0.0333	0.0164	2.0315	0.0423
AR(1)	0.1575	0.0218	7.2167	0.0000
Adj. R^2	0.0229			
D. Watson	1.9580			
Optimistic and Pessimistic Investor Sentiment and Equity Returns– Pakistan				
CONSTANT	-0.0198	0.0193	-1.0253	0.3053
ΔSENTM $*D_1$	1.1017	0.0608	18.1138	0.0000
ΔSENTIM $*D_2$	0.6145	0.0657	9.3560	0.0000
ΔSENTIM^2 $*D_1$	-0.3119	0.0264	-11.8200	0.0000
ΔSENTIM^2 $*D_2$	0.0148	0.0273	0.5422	0.5877
RP	0.0020	0.0014	1.4822	0.1383
AR(1)	0.5194	0.0389	13.3403	0.0000
Adj. R^2	0.1113			
D. Watson	1.9976			
Panel Data Analysis				
CONSTANT	0.0340	0.0166	2.0486	0.0405
ΔSENTM $*D_1$	0.3596	0.0318	11.3044	0.0000
ΔSENTIM $*D_2$	0.1611	0.0312	5.1662	0.0000
ΔSENTIM^2 $*D_1$	-0.0663	0.0076	-8.7397	0.0000
ΔSENTIM^2 $*D_2$	0.0320	0.0074	4.2915	0.0000
RP	0.0021	0.0019	1.1205	0.2625
AR(1)	0.1193	0.0052	22.8652	0.0000
Adj. R^2	0.0210			
D. Watson	2.0033			

ΔSENTIM*D_1 is optimistic investor sentiment in the linear term, ΔSENTIM*D_2 is pessimistic investor sentiment in the linear term, ΔSENTIM2*D_1 is optimistic investor sentiment in the non-linear term, ΔSENTIM2*D_2 is pessimistic investor sentiment in a non-linear term, RP is market premium and AR is Auto Regressive term.

Table 4.4 reports the impact of investor sentiment on equity returns using panel data analysis. In linear settings, optimistic investor sentiment has a significant positive impact on equity returns, suggesting that returns for exuberant investors are increasing as they trade the market. Conversely, a negative link between pessimistic investor sentiment and equity returns leads to market selling pressure and falling market returns. Therefore, optimistic investment behavior results in high returns, and pessimistic investment behavior result in low or negative returns. These results are supported by the studies of Sayim and Rahman (2015) and Verma and Verma (2007). The information in the market, translated into stock returns by investor sentiment, could be the reason for an insignificant and negative coefficient of the market premium given in the table. The significant positive autoregressive term indicates a serial correlation in the series.

In non-linear settings, optimistic investor sentiment has a significant negative impact on equity returns. This indicates that optimistic investor sentiment leads to higher returns in the market, and this relationship is not linear. The negative sign of the quadratic term indicates the relationship is convex, showing that instantly optimistic investor sentiment increases return but reverses beyond a certain level. Similar results are observed by He et al. (2020). Likewise, pessimistic investor sentiment has a significant influence on equity returns. This relationship is also non-linear in nature, which is also reversed subsequently. On the other hand, highly pessimistic investor sentiment instantly decreases return to a certain level and reverses (increases) after a certain level of decrease.

This table also reports the country-specific impact of investor sentiment on equity returns using Auto Regression analysis. In a linear setting, optimistic investor sentiment in Brazil, Russia, Indonesia, China, and Pakistan is having a significant positive impact on equity returns, suggesting optimistic investors in these countries believe they are good in positive situations, anticipate high market prices, indulge themselves in extraordinary buying to get high payoffs and result in above average prices. The results are in accordance with Wang et al. (2022) and Huang et al. (2014). A significant negative impact of investor sentiment on equity returns for South Africa suggests a correction in mispricing over time, while an insignificant negative impact observed for India might be due to a higher proportion of rational investors in the representative market. Pessimistic investor sentiment in Brazil, Indonesia, India, China, South Africa, and Pakistan is also having a significant positive impact on equity returns, suggesting that pessimistic investors in these markets see themselves as more vulnerable to negative situations, foresee low prices, and engage in extraordinary selling to limit their losses and lead to below-average prices as seen by Li (2020). These results are consistent with He et al. (2020). An insignificant impact of pessimistic investor sentiment is observed in Russia, indicating a lower proportion of pessimistic investors in these markets, as observed by Yelamanchili et al. (2019) and Li (2020).

In non-linear terms, optimistic investor sentiment in Brazil, Indonesia, India, China, South Africa, and Pakistan has a significant negative impact on equity returns suggesting that the positive relationship observed in linear terms does not exist all the time, because mispricing so caused does not persist for long periods and tend to revert to fundamental value with time, showing the negative relationship, termed as reversal effect. A significant positive relationship observed in the case of Russia reflects the persistence of mispricing in the market. The insignificant negative relationship observed in the Indian market may be due to the absence of quadratic nature of the relationship between optimistic investor sentiment and equity returns (Brown and Cliff, 2004, 2005).

Pessimistic investor sentiment in Brazil, India, South Africa, and Indonesia shows a significant positive effect on equity returns. The positive relationship between pessimistic investor sentiment and market returns is of a convex nature which means pessimistic investor involves in extraordinary selling for some time that keeps the prices persistently low that time, this phenomenon is called the "momentum effect". The negative relationship between the parameters under discussion observed in Russia indicates that extraordinary selling pressure caused by pessimistic investors is reversed after reaching a certain point through a phenomenon called the "reversal effect". The insignificant relationship between pessimistic investors and market returns is observed in China and Pakistan which might be due to the presence of high strength of optimistic investors in these markets as reported by Kling and Gao (2008).

4.5 Moderate and Extreme Levels of Investor Sentiment and Equity Returns

Table 4.5 represents the impact of moderate levels of investor sentiment, extremely optimistic investor sentiment, and extremely pessimistic investor sentiment on equity returns at the country and group level. To explore the effect of these investor sentiment levels on returns at the country level Auto Regressive-Model is applied and at the group level Dynamic Panel Fixed Effect Model is applied.

TABLE 4.5: Impact of Moderate and Extreme Levels of Investor Sentiment on Equity Returns

Levels of Investor Sentiment and Equity Returns – Brazil				
Variable	**Coefficient**	**Std. Error**	**T-statistic**	**Prob.**
CONSTANT	0.0689	0.0344	1.9999	0.0457
ΔSENTIM	0.1087	0.0605	1.7973	0.0725
Ext. OPT	0.0643	0.1314	0.4890	0.6249
Ext. PES	-0.0103	0.0754	-0.1363	0.8916
AR(1)	0.0536	0.0191	2.8045	0.0051
Adj. R^2	0.0048			
D. Watson	1.9621			
Levels of Investor Sentiment and Equity Returns – Russia				
CONSTANT	0.7119	0.1387	5.1330	0.0000
ΔSENTIM	0.2707	0.0764	3.5419	0.0004
Ext. OPT	-0.4689	0.0530	-8.8473	0.0000
Ext. PES	0.7448	0.2143	3.4750	0.0005
RP	0.0350	0.0139	2.5080	0.0122
AR (1)	0.1287	0.0245	5.2441	0.0000

Adj. R^2	0.0538			
D. Watson	2.1948			
Levels of Investor Sentiment and Equity Returns – Indonesia				
CONSTANT	-0.0721	0.0232	-3.1085	0.0019
ΔSENTIM	-0.0662	0.0128	-5.1734	0.0000
Ext. OPT	0.1565	0.0634	2.4671	0.0137
Ext. PES	0.1194	0.0401	2.9774	0.0029
AR (1)	0.2595	0.0158	16.4365	0.0000
Adj. R^2	0.054094			
D. Watson	2.224784			
Levels of Investor Sentiment and Equity Returns – India				
CONSTANT	0.1735	0.0466	3.7232	0.0002
ΔSENTIM	-0.2100	0.0518	-4.0550	0.0001
Ext. OPT	-0.5386	0.1878	-2.8682	0.0042
Ext. PES	0.1534	0.0615	2.4942	0.0127
AR(1)	0.1145	0.0190	6.0351	0.0000
Adj. R^2	0.0181			
D. Watson	1.6251			
Levels of Investor Sentiment and Equity Returns – China				
CONSTANT	0.0164	0.0226	0.7275	0.4669
ΔSENTIM	0.8991	0.0843	10.6623	0.0000
Ext. OPT	0.6312	0.1616	3.9046	0.0001
Ext. PES	0.3268	0.1263	2.5876	0.0097
Adj. R^2	0.0351			
D. Watson	1.9742			
Levels of Investor Sentiment and Equity Returns – South Africa				
CONSTANT	-0.2577	0.1343	-1.9185	0.0552
ΔSENTIM	0.0422	0.0253	1.6680	0.0955
Ext. OPT	-0.0146	0.1334	-0.1096	0.9128
Ext. PES	-0.1492	0.0358	-4.1728	0.0000
RP	-0.0333	0.0174	-1.9147	0.0557

AR(1)	0.1825	0.0320	5.7029	0.0000
Adj. R^2	0.0216			
D. Watson	2.2025			
Levels of Investor Sentiment and Equity Returns – Pakistan				
CONSTANT	0.1623	0.0568	2.8563	0.0043
ΔSENTIM	0.4965	0.0262	18.9289	0.0000
Ext. OPT	0.2593	0.0566	4.5852	0.0000
Ext. PES	0.0906	0.0487	1.8594	0.0630
RP	0.0130	0.0061	2.1401	0.0324
AR(1)	0.1626	0.0104	15.6116	0.0000
Adj. R^2	0.0867			
D. Watson	2.0251			
Panel Data Analysis				
CONSTANT	0.0242	0.0066	3.6605	0.0003
ΔSENTIM	0.1455	0.0166	8.7505	0.0000
Ext. OPT	0.0476	0.0275	1.7279	0.0840
Ext. PES	-0.0415	0.0211	-1.9701	0.0488
AR(1)	0.4245	0.0410	10.3555	0.0000
AR(2)	1.5232	0.0179	84.6902	0.0000
Adj. R^2	0.0188			
D. Watson	2.0008			

ΔSENTIM is the moderate sentiment index, Ext. OPT is an extremely optimistic investor, Ext. PES is an extremely pessimistic investor, AR is Auto Regressive term. * is significant at 1%.

Table 4.5 represents investor sentiment at a moderate level (ΔSENTIM), extremely optimistic (Ext. OPT), extremely pessimistic (Ext. Pes), market premium (RP), and Auto-Regressive term (AR). To analyze the impact of moderate levels of investor sentiment, extremely optimistic investor sentiment, and extremely pessimistic investor sentiment on equity returns at the country level, the Auto Regressive model is applied. A moderate level of investor sentiment shows a significant positive effect on returns in Brazil, Russia, China, South Africa, and Pakistan, whereas a significant negative effect is observed in Indonesia and India. Brazil, Russia, China, South Africa, and Pakistan exhibit overpricing (underpricing) caused by the activities of optimistic (pessimistic) investors in these markets. Whereas Indonesia and India indicate the reversal effect of mispricing. These significant positive results are aligned with the study of Namouri et al. (2018), and negative results are aligned with the study of Liu et al. (2011).

Extremely optimistic investor sentiment shows a significant positive effect on returns for Indonesia, China, and Pakistan and a significant negative for Russia and India, whereas, in Brazil and South Africa, investor sentiment does not affect the returns. It indicates the dominating role of optimistic investors in the Indonesia, China, and Pakistan markets. Russia and India show correction of mispricing. The insignificant results indicate the non-presence of irrational investors in the market. These significant positive effects are aligned with the study of Namouri et al. (2018) negative effects are aligned with the study of Liu et al. (2011), and insignificant results are aligned with Namouri et al. (2018). Extremely pessimistic investor sentiment has a significant positive effect on Russia, India, China, and Pakistan, a significant negative for South Africa, and an insignificant for Brazil. Positive results observed here represent the continuation of mispricing, whereas negative values reflect the correction of mispricing. The equity markets of Russia, India, and South Africa are revealed to be more efficient and less prone to sentimental effects.

The Dynamic Panel Fixed Effect Model is used to explore the effect of various levels of investor sentiment on returns at the group level. The results reveal that a moderate level of investor sentiment and an extreme level of investor sentiment has a significant positive effect on returns, whereas an extremely pessimistic level of investor sentiment has a negative effect. It indicates that extremely optimistic investors enthusiastically enter the equity markets and invest eagerly in the market during their spans of over-optimism. In contrast, they sell their assets, avoid investments, and wait for opportunities during their over-pessimism. Significant results at an extreme level of optimistic and pessimistic investors are aligned with the study of Li (2020) and Namouri et al. (2018). Significant Auto Regressive terms indicate the Auto-correlation in the series.

4.6 Non-Linear and Linear Impact of Positive and Negative Investor Sentiment on Volatility

Table 4.6 reveals the nonlinear and linear impact of positive and negative investor sentiment on conditional volatility. The GARCH model is applied to generate conditional volatility in the first step. Then the non-linear Auto Regressive Moving Average model is applied to analyze the non-linear and linear relationship between investor sentiment and conditional volatility at the country level. Likewise, the Panel GARCH model is applied to generate conditional volatility for panel data, and then the nonlinear Dynamic Auto Regressive Moving Average model is applied to investigate the nonlinear and linear relation of investor sentiment with volatility.

TABLE 4.6: Impact of Positive and Negative Investor Sentiment on Volatility in Linear and Non-Linear Settings

Investor Sentiment and Conditional Volatility – Brazil				
Variable	**Coefficient**	**Std. Error**	**t-statistic**	**Prob.**
CONSTANT	1.1097	0.1318	8.4191	0.0000
ΔSENTIM*D_1	-0.3090	0.1566	-1.9736	0.0485
ΔSENTIM*D_2	-0.0799	0.1416	-0.5643	0.5726
ΔSENTIM^2* D_1	0.0486	0.0261	1.8598	0.0630
ΔSENTIM^2* D_2	-0.0172	0.0232	-0.7398	0.4594
AR(1)	-0.5838	0.0544	-10.7332	0.0000
AR(2)	0.4371	0.0256	17.0486	0.0000
MA(1)	0.4371	0.0256	17.0486	0.0000
Adj. R^2	0.3051			
D. Watson	2.0004			
Investor Sentiment and Conditional Volatility – Russia				
CONSTANT	-0.3098	0.1637	-1.8931	0.0584
ΔSENTIM*D_1	1.0729	0.2094	5.1233	0.0000
ΔSENTIM*D_2	0.8948	0.2100	4.2601	0.0000
ΔSENTIM^2* D_1	0.1842	0.0965	1.9077	0.0565
ΔSENTIM^2* D_2	0.3154	0.0497	6.3468	0.0000
AR(1)	1.3325	0.0399	33.3699	0.0000
AR(2)	0.4371	0.0256	17.0486	0.0000
Adj. R^2	0.2633			
D. Watson	2.0068			

Investor Sentiment and Conditional Volatility – Indonesia				
CONSTANT	1.3834	0.3786	3.6536	0.0003
ΔSENTIM*D_1	-0.6841	0.1670	-4.0967	0.0000
ΔSENTIM*D_2	0.0462	0.1193	0.3870	0.6988
ΔSENTIM^2* D_1	0.1386	0.0760	1.8230	0.0684
ΔSENTIM^2* D_2	0.0054	0.0615	0.0877	0.9301
AR(1)	-0.3858	0.0768	-5.0254	0.0000
AR(2)	0.9537	0.0072	131.8783	0.0000
MA(1)	-0.2592	0.0793	-3.2664	0.0011
Adj. R^2	0.2232			
D. Watson	1.9933			
Investor Sentiment and Conditional Volatility – India				
CONSTANT	0.2427	0.1595	1.5214	0.1282
ΔSENTIM*D_1	-2.6059	0.1153	-22.5839	0.0000
ΔSENTIM*D_2	0.7923	0.2181	3.6320	0.0003
ΔSENTIM^2* D_1	1.6745	0.0157	106.0162	0.0000
ΔSENTIM^2* D_2	0.2299	0.0540	4.1969	0.0000
AR(1)	0.2506	0.0028	89.4280	0.0000
AR(2)	0.2168	0.0046	46.2926	0.0000
Adj. R^2	0.3180			
D. Watson	2.0066			
Investor Sentiment and Conditional Volatility – China				
CONSTANT	0.2342	0.0295	7.9393	0.0000
ΔSENTIM*D_1	0.9790	0.1407	6.9589	0.0000
ΔSENTIM*D_2	0.5997	0.1873	3.2028	0.0014
ΔSENTIM^2* D_1	0.3493	0.1015	3.4414	0.0006
ΔSENTIM^2* D_2	0.4330	0.1618	2.6763	0.0075
AR(1)	1.1635	0.0400	29.0640	0.0000
AR(2)	-0.4310	0.0272	-15.7924	0.0000
MA(1)	-0.6112	0.0259	-23.5916	0.0000
Adj. R^2	1.1316			
D. Watson	2.0070			
Investor Sentiment and Conditional Volatility – South Africa				
CONSTANT	-0.0132	0.0145	-0.9127	0.3614
ΔSENTIM*D_1	0.2492	0.0376	6.6234	0.0000
ΔSENTIM*D_2	0.1332	0.0385	3.4590	0.0005
ΔSENTIM^2* D_1	-0.0241	0.0106	-2.2644	0.0236
ΔSENTIM^2* D_2	0.0095	0.0116	0.8151	0.4151
AR(1)	1.3024	0.0117	111.1504	0.0000
AR(2)	-0.4075	0.0155	-26.155	0.0000
Adj. R^2	0.2727			
D. Watson	2.0028			

Investor Sentiment and Conditional Volatility – Pakistan				
CONSTANT	0.0436	0.0131	3.3304	0.0009
ΔSENTIM*D_1	0.2203	0.0421	5.2283	0.0000
ΔSENTIM*D_2	0.2237	0.0423	5.2887	0.0000
ΔSENTIM^2* D_1	-0.0108	0.0207	-0.5222	0.6016
ΔSENTIM^2* D_2	0.0991	0.0149	6.6458	0.0000
AR(1)	0.7015	0.0097	72.3095	0.0000
AR(2)	0.3495	0.0157	22.1664	0.0000
MA(1)	-0.8857	0.0095	-92.5207	0.0000
Adj. R^2	0.1873			
D. Watson	2.0051			
Panel Data Analysis				
CONSTANT	0.0579	0.0060	9.6054	0.0000
ΔSENTIM*D_1	-0.0844	0.0184	-4.5719	0.0000
ΔSENTIM*D_2	-0.0434	0.0175	-2.4813	0.0131
ΔSENTIM^2* D_1	0.0360	0.0042	8.4991	0.0000
ΔSENTIM^2* D_2	-0.0085	0.0040	-2.1196	0.0000
AR(1)	0.9762	0.0011	866.0575	0.0000
Adj. R^2	0.9538			
D. Watson	1.8091			

ΔSENTIM*D_1 is optimistic investor sentiment in the linear term, ΔSENTIM*D_2 is pessimistic investor sentiment in the linear term, ΔSENTIM2*D_1 is optimistic investor sentiment in the non-linear term, ΔSENTIM2*D_2 is pessimistic investor sentiment in a non-linear term, AR is Auto Regressive term and MA is Moving Average term.

In linear settings, optimistic and pessimistic investor sentiments positively correlate with conditional volatility in Russia, China, South Africa, and Pakistan. It means both optimistic and pessimistic investor sentiments in these countries symmetrically increase the volatility. A negative correlation between optimistic investor sentiment and volatility exists in Brazil, India, and Indonesia indicating that an increase in bullish investor sentiment symmetrically decreases the volatility. Whereas, a negative correlation between pessimistic investor sentiment and volatility exists in India which indicates that an increase in bearish investor sentiment symmetrically increases the volatility. In Indonesia and Brazil, negative investor sentiment does not correlate with volatility meaning sentiments of pessimistic investors have no role in creating the volatility. The symmetric positive relation of investor sentiment with volatility is also observed by Yu and Yuan (2011), and the symmetric negative relation between the two is observed by Labidi and Yaakoubi (2016).

In nonlinear settings, the relation of positive investor sentiment with volatility is positive for Brazil, Russia, Indonesia, India, and China, whereas negative for South Africa, and there is no relation for Pakistan.

It indicates that changes in bullish investor sentiment asymmetrically increase the volatility in Brazil, Russia, Indonesia, India, and China and decrease the volatility in South Africa and vice versa.

The relation of bearish investor sentiment with volatility is positive for Russia, India, China, and Pakistan. It indicates that bearish investor sentiment asymmetrically increases the volatility in these markets.

In Brazil, Indonesia, and South Africa, this relationship is insignificant revealing the absence of bearish investor sentiment. A positive relation between investor sentiment and volatility supports the findings of Shen et al. (2017), negative relation supports the findings of Wang et al. (2022).

At the group level and linear settings, bullish and bearish investor sentiment negatively relates to volatility. It means an increase in the level of bullish sentiment decreases the volatility, whereas, an increase in the level of bearish sentiment increases the volatility.

In nonlinear settings, bullish investor sentiment has a positive relation, and bearish investor sentiment has a negative relation with volatility.

This reveals that investor sentiment has an asymmetric effect on volatility. Generally, the reason behind the increase in volatility is the pessimistic behavior of the investor, who is fearful of future prospects, which increases uncertainty in the markets.

Role of Investor Sentiment on the Relationship between Market Risk and Equity Returns

Market risk is evaluated through VaR and CVaR at 95% and 99% confidence levels. Auto-Regressive and Moving Average models are applied to explore the mutual relationship of all three variables.

4.7 Investor Sentiment, Value at Risk at 95% Confidence Level, and Equity Returns

Table 4.7 reports the effect of optimistic and pessimistic investor sentiment on the relationship between VaR-95 and equity returns.

TABLE 4.7: Effect of Optimistic and Pessimistic Investor Sentiment on the Relationship between VaR-95 and Equity Returns

Investor Sentiment, Value at Risk at 95% and Equity Returns– Brazil				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
CONSTANT	-0.0743	0.1775	-0.4187	0.6755
VaR95	-0.0705	0.0508	-1.3880	0.1653
ΔSENTM *OPT	0.1338	0.0755	1.7718	0.0766
ΔSENTIM *PES	-0.5932	0.3377	-1.7565	0.0792
Var95*ΔSENTIM*OPT	0.0542	0.0203	2.6707	0.0076
Var95*ΔSENTIM*PES	-0.2836	0.0984	-2.8812	0.0040
AR(1)	0.1157	0.0235	4.9185	0.0000
Adj. R^2	0.0229			
D. Watson	2.0617			
Investor Sentiment, Value at Risk at 95% and Equity Returns– Russia				
CONSTANT	0.0763	0.0550	1.3730	0.1690
VaR95	0.0067	0.0140	0.4730	0.6360
ΔSENTM *OPT	-0.4636	0.2182	-2.1240	0.0330
ΔSENTIM *PES	-0.4525	0.1750	-2.5790	0.0090
Var95*ΔSENTIM*OPT	-0.2214	0.0520	-4.2030	0.0000
Var95*ΔSENTIM*PES	-0.0755	0.0450	-1.6600	0.0960
AR(1)	0.1580	0.0130	11.5430	0.0000
Adj. R^2	0.0297			
D. Watson	1.9929			
Investor Sentiment, Value at Risk at 95% and Equity Returns – Indonesia				
CONSTANT	0.0220	0.0285	0.7706	0.4410
VaR95	-0.0027	0.0088	-0.3115	0.7554
ΔSENTM *OPT	-0.0266	0.0882	-0.3015	0.7630
ΔSENTIM *PES	-0.1410	0.1056	-1.3346	0.1821
Var95*ΔSENTIM*OPT	-0.1091	0.0261	-4.1883	0.0000

Var95*ΔSENTIM*PES	-0.1867	0.0284	-6.5673	0.0000
AR(1)	0.8922	0.0500	17.8583	0.0000
Adj. R^2	0.0526			
D. Watson	1.9978			
Investor Sentiment, Value at Risk at 95% and Equity Returns – India				
CONSTANT	-0.2129	0.0578	-3.6817	0.0002
VaR95	-0.0473	0.0167	-2.8276	0.0047
ΔSENTM *OPT	0.1065	0.0777	1.3715	0.1703
ΔSENTIM *PES	-0.3581	0.1055	-3.3946	0.0007
Var95*ΔSENTIM*OPT	0.0294	0.0167	1.7596	0.0785
Var95*ΔSENTIM*PES	0.0890	0.0311	2.8650	0.0042
AR(1)	0.1909	0.0145	13.2114	0.0000
Adj. R^2	0.0764			
D. Watson	2.1168			
Investor Sentiment, Value at Risk at 95% and Equity Returns – China				
CONSTANT	-0.0472	0.0607	-0.7787	0.4362
VaR95	0.0262	0.0157	1.6627	0.0964
ΔSENTM *OPT	0.8533	0.1698	5.0265	0.0000
ΔSENTIM *PES	-0.5049	0.2511	-2.0107	0.0444
Var95*ΔSENTIM*OPT	-0.3418	0.0435	-7.8589	0.0000
Var95*ΔSENTIM*PES	-0.2236	0.0600	-3.7261	0.0002
AR(1)	0.1973	0.0213	9.2693	0.0000
Adj. R^2	0.0535			
D. Watson	2.0041			
Investor Sentiment, Value at Risk at 95% and Equity Returns – South Africa				
CONSTANT	-0.1985	0.0711	-2.7927	0.0052
VaR95	-0.1148	0.0175	-6.5622	0.0000
ΔSENTM *OPT	0.1496	0.0368	4.0622	0.0000
ΔSENTIM *PES	-0.0942	0.0413	-2.2837	0.0224
Var95*ΔSENTIM*OPT	0.0959	0.0092	10.3751	0.0000
Var95*ΔSENTIM*PES	-0.0525	0.0079	-6.6304	0.0000
AR(1)	-0.7974	0.0196	-40.7271	0.0000
Adj. R^2	0.0170			
D. Watson	2.0023			

Investor Sentiment, Value at Risk at 95% and Equity Returns – Pakistan				
CONSTANT	-0.0076	0.0232	-0.3291	0.7421
VaR95	-0.0041	0.0070	-0.5820	0.5606
ΔSENTM *OPT	-0.0849	0.0643	-1.3204	0.1868
ΔSENTIM *PES	-0.1252	0.0955	-1.3110	0.1899
Var95*ΔSENTIM*OPT	-0.3428	0.0201	-17.0697	0.0000
Var95*ΔSENTIM*PES	-0.3231	0.0268	-12.0515	0.0000
AR(1)	0.4707	0.0299	15.7408	0.0000
Adj. R^2	0.1299			
D. Watson	1.9976			
Panel Data Analysis				
CONSTANT	0.0428	0.0179	2.3915	0.0168
VaR95	0.0048	0.0061	0.7920	0.4284
ΔSENTM *OPT	-0.0033	0.0408	-0.0800	0.9362
ΔSENTIM *PES	-0.0753	0.0441	-1.7058	0.0880
Var95*ΔSENTIM*OPT	-0.0610	0.0131	-4.6650	0.0000
Var95*ΔSENTIM*PES	-0.0605	0.0145	-4.1845	0.0000
AR(1)	0.1199	0.0052	22.9089	0.0000
Adj. R^2	0.0195			
D. Watson	0.0195			

ΔSENTM *OPT is optimistic investor sentiment, ΔSENTIM *PES is pessimistic investor sentiment, VaR95 is Value at risk at 95% confidence interval, Var95*ΔSENTIM*OPT is interaction term of Value at Risk at 95% level, and optimistic investor sentiment and AR is Auto Regressive term.

Table 4.7 reveals that the effect of optimistic investor sentiment on the relationship between market risk and equity returns is positive for Brazil, India, and South Africa and negative for Russia, Indonesia, China, and Pakistan. Similarly, the results are negative at the group level. The positive relationship between VaR-95 and equity returns observed in the case of Brazil, India, and South Africa means that investors in these countries, during high sentiment periods, are more confident and take high risks in trading the assets that have the potential to result in high returns in the future. Therefore, they earn returns higher than the expected average returns. The negative relationship observed in the case of Russia, Indonesia, China, and Pakistan reveals that investors in these countries, being more overconfident and expecting abnormal returns, trade-in high-risk stocks without considering the potential risk related to those stocks and hence gain lower profits than the potential gains or in other words bear losses.

The effect of pessimistic investor sentiment on the relation of VaR-95 and equity returns is negative when taken at the group and country levels, except for India, where it is positive. The negative relationship observed at the country level and the group level reveals that investors in these countries, during low sentiment periods, are more conservative, and trade in the less risky assets, which increases the demand for these assets and results in higher returns in the future. The positive relationship observed in the case of India is likely due to the demand for high premiums, by the investors, against the risk they bear and, therefore, earn higher gains. The positive effect of investor sentiment on the relationship between volatility and equity returns is also observed by Yu (2021) & He et al. (2019), and the negative relation between the two is observed by Labidi and Yaakoubi (2016).

4.8 Investor Sentiment, Value at Risk at 99% Confidence Level and Equity Returns

Table 4.8 reports the effect of optimistic and pessimistic investor sentiment on the relationship between VaR-99 and equity returns.

TABLE 4.8: Effect of Optimistic and Pessimistic Investor Sentiment on the Relationship between VaR-99 and Equity Returns

Investor Sentiment, Value at Risk at 99% and Equity Returns – Brazil				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
CONSTANT	-0.0743	0.1775	-0.4187	0.6755
VaR99	-0.0598	0.0431	-1.3880	0.1653
ΔSENTM *opt	0.1338	0.0755	1.7718	0.0766
ΔSENTIM *PES	-0.5932	0.3377	-1.7565	0.0792
Var99*ΔSENTIM*OPT	0.0459	0.0172	2.6707	0.0076
Var99*ΔSENTIM*PES	-0.2407	0.0835	-2.8812	0.0040
AR(1)	0.1157	0.0235	4.9185	0.0000

Adj. R^2	0.0229			
D. Watson	2.0617			
Investor Sentiment, Value at Risk at 99% and Equity Returns – Russia				
CONSTANT	0.0763	0.0555	1.3740	0.1695
VaR99	0.0057	0.0120	0.4730	0.6362
ΔSENTM *OPT	-0.4636	0.2182	-2.1245	0.0337
ΔSENTIM *PES	-0.4525	0.1754	-2.5791	0.0099
Var99*ΔSENTIM*OPT	-0.1878	0.0447	-4.2031	0.0000
Var99*ΔSENTIM*PES	-0.0640	0.0386	-1.6603	0.0969
AR(1)	0.1580	0.0137	11.5430	0.0000
Adj. R^2	0.0297			
D. Watson	1.9929			
Investor Sentiment, Value at Risk at 99% and Equity Returns – Indonesia				
CONSTANT	0.0220	0.0285	0.7706	0.4410
VaR99	-0.0023	0.0074	-0.3115	0.7554
ΔSENTM *OPT	-0.0266	0.0882	-0.3015	0.7630
ΔSENTIM *PES	-0.1410	0.1056	-1.3346	0.1821
Var99*ΔSENTIM*OPT	-0.0926	0.0221	-4.1883	0.0000
Var99*ΔSENTIM*PES	-0.1584	0.0241	-6.5673	0.0000
AR(1)	0.8922	0.0500	17.8583	0.0000
Adj. R^2	0.0526			
D. Watson	1.9978			
Investor Sentiment, Value at Risk at 99% and Equity Returns – India				
CONSTANT	-0.2129	0.0578	-3.6817	0.0002
VaR99	-0.0402	0.0142	-2.8276	0.0047
ΔSENTM *OPT	0.1065	0.0777	1.3715	0.1703
ΔSENTIM *PES	-0.3581	0.1055	-3.3946	0.0007
Var99*ΔSENTIM*OPT	0.0250	0.0142	1.7596	0.0785
Var99*ΔSENTIM*PES	0.0755	0.0264	2.8650	0.0042
AR(1)	0.1909	0.0145	13.2114	0.0000
Adj. R^2	0.0764			
D. Watson	2.1168			
Investor Sentiment, Value at Risk at 99% and Equity Returns – China				
CONSTANT	-0.0472	0.0607	-0.7787	0.4362

VaR99	0.0222	0.0134	1.6627	0.0964
ΔSENTM *OPT	0.8533	0.1698	5.0265	0.0000
ΔSENTIM *PES	-0.5049	0.2511	-2.0107	0.0444
Var99*ΔSENTIM*OPT	-0.2900	0.0369	-7.8589	0.0000
Var99*ΔSENTIM*PES	-0.1898	0.0509	-3.7261	0.0002
AR(1)	0.1973	0.0213	9.2693	0.0000
Adj. R^2	0.0535			
D. Watson	2.0041			
Investor Sentiment, Value at Risk at 99% and Equity Returns – South Africa				
CONSTANT	-0.1985	0.0711	-2.7927	0.0052
VaR99	-0.0974	0.0148	-6.5622	0.0000
ΔSENTM *OPT	0.1496	0.0368	4.0622	0.0000
ΔSENTIM *PES	-0.0942	0.0413	-2.2837	0.0224
Var99*ΔSENTIM*OPT	0.0814	0.0078	10.3751	0.0000
Var99*ΔSENTIM*PES	-0.0446	0.0067	-6.6304	0.0000
AR(1)	-0.7974	0.0196	-40.7271	0.0000
Adj. R^2	0.0170			
D. Watson	2.0023			
Investor Sentiment, Value at Risk at 99% and Equity Returns – Pakistan				
CONSTANT	-0.0076	0.0232	-0.3291	0.7421
VaR99	-0.0034	0.0059	-0.5820	0.5606
ΔSENTM *OPT	-0.0849	0.0643	-1.3204	0.1868
ΔSENTIM *PES	-0.1252	0.0955	-1.3110	0.1899
Var99*ΔSENTIM*OPT	-0.2909	0.0170	-17.0697	0.0000
Var99*ΔSENTIM*PES	-0.2741	0.0227	-12.0516	0.0000
AR(1)	0.4707	0.0299	15.7408	0.0000
Adj. R^2	0.1299			
D. Watson	1.9976			
Panel Data Analysis				
CONSTANT	0.0428	0.0179	2.3915	0.0168
VaR99	0.0041	0.0051	0.7920	0.4284
ΔSENTM *OPT	-0.0033	0.0408	-0.0800	0.9362
ΔSENTIM *PES	-0.0753	0.0441	-1.7058	0.0880
Var99*ΔSENTIM*OPT	-0.0517	0.0111	-4.6650	0.0000

Var99*ΔSENTIM*PES	-0.0514	0.0123	-4.1845	0.0000
AR(1)	0.1199	0.0052	22.9089	0.0000
Adj. R^2	0.0195			
D. Watson	2.0023			

ΔSENTM *OPT is optimistic investor sentiment, ΔSENTIM *PES is pessimistic investor sentiment, VaR99 is Value at risk at 99% confidence interval, Var95*ΔSENTIM*OPT is interaction term of Value at Risk at 99% level, and optimistic investor sentiment and AR is Auto Regressive term.

It is evident from Table 4.8 that Russia, Indonesia, China, and Pakistan show a negative relationship between VaR-99 and returns under the spans of high investor sentiment, whereas Brazil, India, and South Africa show a positive relationship between the two. The negative relationship is also observed at the aggregate level. The negative effect, during high sentiment periods, is due to investors' over-cautious and conservative behavior in these markets. They do not take additional risks and lose the opportunity of gaining potential returns and, as a result, gain returns lower than the average market returns. The positive relationship between the VaR-99 and return reveal that investors in these countries are overconfident, buy highly risky stocks during their high sentiment periods, and expect high returns from such stocks, hence resulting in high profits. The negative effect during spans of high sentiment is aligned with the study of Piccoli et al. (2018) and the positive effect is aligned with the study of He et al. (2019).

A negative effect of pessimistic investor sentiment on the relation of VaR-99 and returns is observed at an aggregate level and the country level in all the countries except India. This negative effect reveals that investors in these countries, during low sentiment periods, are more conservative and do not take risks in trading the assets that have the potential to result in low returns in the future. Therefore, they earn returns higher than the expected average returns. The positive effect in India reveals that pessimistic investors in these markets are more cautious about their investments, therefore demand high returns against the risk they take, and hence gain higher profits than the average gains. The positive relationship between variance and equity returns during spans of low sentiment is aligned with the study of Piccoli et al. (2018) & Wang (2020) and negative is aligned with the study of Ahmed et al. (2012).

4.9 Investor Sentiment, Conditional Value at Risk at a 95% Confidence Level, and Equity Returns

Table 4.9 reports the effect of high and low levels of investor sentiment on the relationship between equity returns and CVaR-95.

Table 4.9: Effect of High and Low Investor Sentiment on the Relationship between Equity Returns and C-VaR-95

Investor Sentiment, Conditional Value at Risk at 95%, and Equity Returns – Brazil				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
CONSTANT	-0.0009	0.0013	-0.6784	0.4976
CVaR-95	-0.0815	0.0407	-2.0004	0.0456
ΔSENTIM *OPT	0.0016	0.0008	2.1114	0.0349
ΔSENTIM*PES	-0.0024	0.0028	-0.8726	0.3830
CVaR-95*ΔSENTIM *OPT	0.0720	0.0241	2.9834	0.0029
CVaR-95*ΔSENTIM *PES	-0.2005	0.0896	-2.2385	0.0253
AR(1)	0.1206	0.0238	5.0583	0.0000
Adj. R^2	0.0223			
D. Watson	2.0702			
Investor Sentiment, Conditional Value at Risk at 95%, and Equity Returns – Russia				
CONSTANT	-0.0005	0.0006	-0.8281	0.4076
CVaR-95	-0.0380	0.0144	-2.6327	0.0085
ΔSENTIM *OPT	-0.0039	0.0022	-1.7766	0.0757
ΔSENTIM*PES	-0.0045	0.0010	-4.3792	0.0000
CVaR-95*ΔSENTIM *OPT	-0.1584	0.0437	-3.6265	0.0003
CVaR-95*ΔSENTIM *PES	0.0574	0.0266	2.1561	0.0311
AR(1)	0.1269	0.0144	8.8332	0.0000
Adj. R^2	0.0405			
D. Watson	2.0425			
Investor Sentiment, Conditional Value at Risk at 95%, and Equity Returns – Indonesia				
CONSTANT	0.0015	0.0004	3.6552	0.0003
CVaR-95	0.1084	0.0195	5.5576	0.0000
ΔSENTIM *OPT	-0.0046	0.0005	-8.7593	0.0000
ΔSENTIM*PES	0.0010	0.0007	1.5521	0.1207

CVaR-95*ΔSENTIM *OPT	-0.4457	0.0360	-12.3646	0.0000
CVaR-95*ΔSENTIM *PES	0.0970	0.0321	3.0224	0.0025
AR(1)	0.1224	0.0144	8.5101	0.0000
Adj. R^2	0.0499			
D. Watson	1.9649			
Investor Sentiment, Conditional Value at Risk at 95%, and Equity Returns – India				
CONSTANT	-0.0008	0.0008	-0.9813	0.3265
CVaR-95	-0.1114	0.0257	-4.3322	0.0000
ΔSENTIM *OPT	-0.0014	0.0011	-1.2288	0.2193
ΔSENTIM*PES	-0.0066	0.0015	-4.4185	0.0000
CVaR-95*ΔSENTIM *OPT	0.0379	0.0425	0.8911	0.3730
CVaR-95*ΔSENTIM *PES	-0.4234	0.0479	-8.8375	0.0000
AR(1)	0.2018	0.0205	9.8311	0.0000
Adj. R^2	0.0658			
D. Watson	2.1630			
Investor Sentiment, Conditional Value at Risk at 95%, and Equity Returns – China				
CONSTANT	-0.0002	0.0006	-0.3499	0.7265
CVaR-95	0.0710	0.0194	3.6574	0.0003
ΔSENTIM *OPT	0.0052	0.0015	3.5507	0.0004
ΔSENTIM*PES	-0.0110	0.0021	-5.1487	0.0000
CVaR-95*ΔSENTIM *OPT	-0.2028	0.0376	-5.3956	0.0000
CVaR-95*ΔSENTIM *PES	-0.2632	0.0566	-4.6498	0.0000
AR(1)	0.1053	0.0143	7.3552	0.0000
Adj. R^2	0.0600			
D. Watson	2.0295			
Investor Sentiment, Conditional Value at Risk at 95%, and Equity Returns – South Africa				
CONSTANT	-0.0035	0.0008	-4.5328	0.0000
CVaR-95	-0.1631	0.0257	-6.3501	0.0000
ΔSENTIM *OPT	0.0010	0.0005	2.1911	0.0285
ΔSENTIM*PES	-0.0021	0.0011	-1.8929	0.0585
CVaR-95*ΔSENTIM *OPT	0.0616	0.0185	3.3250	0.0009
CVaR-95*ΔSENTIM *PES	-0.0949	0.0312	-3.0452	0.0023
AR(1)	0.0976	0.0202	4.8370	0.0000
AR(2)	0.0727	0.0201	3.6187	0.0003
Adj. R^2	0.0254			
D. Watson	2.2905			
Investor Sentiment, Conditional Value at Risk at 95%, and Equity Returns – Pakistan				
CONSTANT	0.0005	0.0004	1.3602	0.1738
CVaR-95	0.0216	0.0123	1.7650	0.0776
ΔSENTIM *OPT	0.0019	0.0008	2.3650	0.0181
ΔSENTIM*PES	0.0019	0.0010	1.8268	0.0678
CVaR-95*ΔSENTIM *OPT	-0.2815	0.0287	-9.8065	0.0000

CVaR-95*ΔSENTIM *PES	-0.2083	0.0336	-6.2059	0.0000
AR(1)	0.5954	0.0200	29.7042	0.0000
MA(1)	-0.4521	0.0230	-19.6957	0.0000
Adj. R^2	0.1208			
D. Watson	1.9833			
Panel Data Analysis				
CONSTANT	0.0006	0.0002	3.4259	0.0006
CVaR-95	0.0106	0.0061	1.7520	0.0798
ΔSENTIM *OPT	0.0005	0.0004	1.3865	0.1656
ΔSENTIM*PES	-0.0004	0.0004	-0.8872	0.3750
CVaR-95*ΔSENTIM *OPT	-0.0479	0.0141	-3.3870	0.0007
CVaR-95*ΔSENTIM *PES	-0.0505	0.0145	-3.4890	0.0005
AR(1)	0.1239	0.0053	23.4896	0.0000
Adj. R^2	0.0183			
D. Watson	2.0073			

ΔSENTM *OPT is optimistic investor sentiment, ΔSENTIM *PES is pessimistic investor sentiment, CVaR95 is Conditional Value at risk at a 95% confidence interval, CVar95*ΔSENTIM*OPT is interaction term of Conditional Value at Risk at 95% level, and optimistic investor sentiment and AR is Auto Regressive term.

Table 4.9 indicates that optimistic investor sentiment has a significant positive effect on the relationship between CVaR at 95% confidence interval and equity returns in Brazil, and South Africa; a negative effect in Russia, Indonesia, China, and Pakistan; and an insignificant effect in India.

The significant negative effect is also visible at an aggregate level. The positive effect seen here is that optimistic investors make bold decisions and invest in risky assets which have higher potential for returns, and thus their optimism leads to higher returns. The negative effect of optimistic investor sentiment seen in Russia, Indonesia, China, and Pakistan indicates that investors in these stock markets do not focus on downside risk and resultantly underestimate the CVaR and overestimate the expected returns, leading to increased exposure to potential losses.

The insignificant effect of investor sentiment observed in India is attributed to other market factors dominating investors' sentiments in these markets. These results also reveal that a shift in optimistic and pessimistic investor sentiment further strengthens the relationship between CVaR and equity returns in the selected emerging markets. Pessimistic investor sentiment significantly negatively affects the relationship between CVaR-95 and equity returns in Brazil, India, China, South

Africa, Pakistan and the aggregate level whereas it significantly positively affects the relationship between CVaR-95 and equity returns in Russia and Indonesia.

It means pessimistic investors prefer more safe assets with low risk of loss which increases demand for less risky assets, that in turn, provide an opportunity for high returns. The positive results are aligned with the study of Hu and Sun (2021) and negative results are aligned with the study of Labidi and Yaakoubi (2016).

4.10 Investor Sentiment, Conditional Value at Risk at a 99% Confidence Level, and Equity Returns

Table 4.10 reports the effect of high and low levels of investor sentiment on the relationship between equity returns and C-VaR-99.

TABLE 4.10: Effect of High and Low Investor Sentiment on the Relationship between Equity Returns and C-VaR-99

Investor Sentiment, Conditional Value at Risk at 99%, and Equity Returns – Brazil				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
CONSTANT	-0.0006	0.0013	-0.4997	0.6173
CVaR-99	-0.0640	0.0345	-1.8517	0.0642
ΔSENTIM *OPT	0.0010	0.0008	1.3337	0.1825
ΔSENTIM*PES	-0.0022	0.0027	-0.8197	0.4125
CVaR-99*ΔSENTIM *OPT	0.0451	0.0208	2.1651	0.0305
CVaR-99*ΔSENTIM *PES	-0.1670	0.0742	-2.2510	0.0245
AR(1)	0.1197	0.0239	5.0130	0.0000
Adj. R^2	0.0204			
D. Watson	2.0659			
Investor Sentiment, Conditional Value at Risk at 99%, and Equity Returns – Russia				
CONSTANT	-0.0002	0.0006	-0.3626	0.7169
CVaR-99	-0.0248	0.0116	-2.1328	0.0330
ΔSENTIM *OPTs	-0.0013	0.0021	-0.6300	0.5287
ΔSENTIM*PES	-0.0045	0.0010	-4.6370	0.0000
CVaR-99*ΔSENTIM *OPT	-0.0758	0.0331	-2.2906	0.0220
CVaR-99*ΔSENTIM *PES	0.0470	0.0208	2.2576	0.0240
AR(1)	0.1292	0.0145	8.9233	0.0000
Adj. R^2	0.0398			
D. Watson	2.0520			

Investor Sentiment, Conditional Value at Risk at 99%, and Equity Returns – Indonesia				
CONSTANT	0.0013	0.0004	3.5168	0.0004
CVaR-99	0.0811	0.0147	5.5147	0.0000
ΔSENTIM *OPT	-0.0043	0.0005	-8.9508	0.0000
ΔSENTIM*PES	0.0012	0.0006	2.0605	0.0394
CVaR-99*ΔSENTIM *OPT	-0.3506	0.0264	-13.2559	0.0000
CVaR-99*ΔSENTIM *PES	0.0873	0.0224	3.8940	0.0001
AR(1)	0.1087	0.0144	7.5472	0.0000
Adj. R^2	0.0510			
D. Watson	1.9621			
Investor Sentiment, Conditional Value at Risk at 99%, and Equity Returns – India				
CONSTANT	-0.0006	0.0007	-0.8294	0.4070
CVaR-99	-0.0927	0.0205	-4.5122	0.0000
ΔSENTIM *OPTs	-0.0019	0.0011	-1.7585	0.0788
ΔSENTIM*PES	-0.0051	0.0015	-3.4837	0.0005
CVaR-99*ΔSENTIM *OPT	0.0097	0.0332	0.2921	0.7703
CVaR-99*ΔSENTIM *PES	-0.3001	0.0387	-7.7540	0.0000
AR(1)	0.1640	0.0207	7.9132	0.0000
AR(2)	0.0764	0.0204	3.7343	0.0002
Adj. R^2	0.0563			
D. Watson	2.1398			
Investor Sentiment, Conditional Value at Risk at 99%, and Equity Returns – China				
CONSTANT	-0.0003	0.0006	-0.5465	0.5847
CVaR-99	0.0588	0.0167	3.5215	0.0004
ΔSENTIM *OPT	0.0045	0.0015	2.9111	0.0036
ΔSENTIM*PES	-0.0111	0.0023	-4.8198	0.0000
CVaR-99*ΔSENTIM *OPT	-0.1956	0.0348	-5.6165	0.0000
CVaR-99*ΔSENTIM *PES	-0.1993	0.0483	-4.1240	0.0000
AR(1)	0.1039	0.0141	7.3418	0.0000
Adj. R^2	0.0576			
D. Watson	2.0294			
Investor Sentiment, Conditional Value at Risk at 99%, and Equity Returns – South Africa				
CONSTANT	-0.0035	0.0008	-4.5252	0.0000
CVaR-99	-0.1505	0.0234	-6.4413	0.0000
ΔSENTIM *OPT	0.0011	0.0005	2.4362	0.0149
ΔSENTIM*PES	-0.0021	0.0011	-1.9623	0.0498
CVaR-99*ΔSENTIM *OPT	0.0615	0.0168	3.6578	0.0003
CVaR-99*ΔSENTIM *PES	-0.0896	0.0281	-3.1848	0.0015
AR(1)	0.0908	0.0202	4.4975	0.0000
AR(2)	0.0681	0.0202	3.3777	0.0007
Adj. R^2	0.0242			
D. Watson	2.2858			

Investor Sentiment, Conditional Value at Risk at 99%, and Equity Returns – Pakistan				
CONSTANT	0.0004	0.0004	0.9947	0.3199
CVaR-99	0.0106	0.0111	0.9609	0.3367
ΔSENTIM *OPT	0.0023	0.0009	2.6224	0.0088
ΔSENTIM*PES	0.0021	0.0011	1.9612	0.0499
CVaR-99*ΔSENTIM *OPT	-0.2218	0.0261	-8.5091	0.0000
CVaR-99*ΔSENTIM *PES	-0.1742	0.0313	-5.5751	0.0000
AR(1)	0.6145	0.0210	29.3287	0.0000
MA(1)	-0.4855	0.0239	-20.3202	0.0000
Adj. R^2	0.1143			
D. Watson	1.9668			
Panel Data Analysis				
CONSTANT	0.0005	0.0002	3.2409	0.0012
CVaR-99	0.0057	0.0051	1.1177	0.2637
ΔSENTIM *OPT	0.0002	0.0004	0.5039	0.6143
ΔSENTIM*PES	-0.0001	0.0004	-0.2236	0.8231
CVaR-99*ΔSENTIM *OPT	-0.0540	0.0122	-4.4242	0.0000
CVaR-99*ΔSENTIM *PES	-0.0338	0.0123	-2.7445	0.0061
AR(1)	0.1138	0.0053	21.4605	0.0000
Adj. R^2	0.0159			
D. Watson	2.0014			

ΔSENTM *OPT is optimistic investor sentiment, ΔSENTIM *PES is pessimistic investor sentiment, CVaR99 is Conditional Value at risk at a 95% confidence interval, CVar99*ΔSENTIM*OPT is interaction term of Conditional Value at Risk at 99% level, and optimistic investor sentiment and AR is Auto Regressive term.

Table 4.10 shows that optimistic investor sentiment has a significant positive effect on the relationship between CVaR-99 and equity returns in Brazil and South Africa, a significant negative effect in Russia, Indonesia, China, Pakistan, and an insignificant effect in India. It means that optimistic investors in the equity markets of Brazil and South Africa are more willing to take higher risks, compensating with higher expected returns. The probable reason for the negative effect observed in the markets of Russia, Indonesia, China, and Pakistan, is ignorance of bad news about the market, biased attitude toward good news, underestimation of risk, and false expectation of returns by the investors, which ultimately results in low returns. The insignificant effect observed in India is linked to many other macroeconomic and fundamental factors prevalent in the equity markets.

Pessimistic investor sentiment has a significant positive effect on the relationship between risk and equity returns in Russia and Indonesia, whereas, negative in

Brazil, India, China, South Africa, and Pakistan. The positive effect of pessimistic investors is due to the creation of mispricing in the market, which provides the opportunity to investors to take high risks to gain high returns. The negative effect of pessimistic investors is due to their demand for undue high returns compared to the risk they take. When the effect of investor sentiment on the relation of CVaR with equity returns is analyzed at the aggregate level, optimistic and pessimistic investor sentiments have a negative effect. The positive results are aligned with the study of Hu et al. (2021) & Wang et al. (2020) and negative results are aligned with the study of Ahmed et al. (2012).

4.11 Macroeconomic Factors, Investor Sentiment and Equity Returns

Table 4.11 reports the effect of bullish and bearish investor sentiment, risk-free rate, industrial production index, and term spread on returns. To analyze the effect of macro factors on the relationship of investor sentiment with equity returns at the country level, the Auto Regressive model is applied, and at the aggregate level Dynamic Panel Fixed Effect model is applied.

TABLE 4.11: The Moderating Effect of Macro Factors on the Relationship of Bullish and Bearish Investor Sentiment with Equity Returns

Macro Factors, Investor Sentiment, and Equity Returns – Brazil				
Variable	**Coefficient**	**Std. Error**	**T-statistic**	**Prob.**
CONSTANT	-0.8027	0.6019	-1.3336	0.1825
ΔSENTIM*OPT	-0.5714	0.2334	-2.4483	0.0144
ΔSENTIM*TB*OPT	0.0107	0.0096	1.1077	0.2681
ΔSENTIM *IPI*OPT	0.0045	0.0021	2.1711	0.0301
ΔSENTIM *TS*OPT	-0.0352	0.0150	-2.3480	0.0190
ΔSENTIM *PES	0.0167	1.1119	0.0150	0.9880
ΔSENTIM *TB*PES	0.0295	0.0281	1.0507	0.2935
ΔSENTIM *IPI*PES	-0.0026	0.0101	-0.2612	0.7940
ΔSENTIM *TS*PES	-0.0264	0.0229	-1.1519	0.2495
AR(1)	0.0888	0.0227	3.9090	0.0001
Adj. R^2	0.0130			

D. Watson	1.9528			
Macro Factors, Investor Sentiment, and Equity Returns – Russia				
CONSTANT	0.7789	0.3450	2.2578	0.0240
ΔSENTIM*OPT	0.7756	0.4997	1.5521	0.1207
ΔSENTIM*TB*OPT	-0.0354	0.0152	-2.3308	0.0198
ΔSENTIM *IPI*OPT	-0.0037	0.0028	-1.3532	0.1761
ΔSENTIM *TS*OPT	-0.0790	0.0379	-2.0813	0.0375
ΔSENTIM *PES	-0.2068	0.5525	-0.3744	0.7081
ΔSENTIM *TB*PES	0.0888	0.0166	5.3590	0.0000
ΔSENTIM *IPI*PES	-0.0024	0.0032	-0.7528	0.4516
ΔSENTIM *TS*PES	0.0125	0.0398	0.3147	0.7530
AR(1)	-0.6268	0.0473	-13.2415	0.0000
Adj. R^2	0.0317			
D. Watson	0.0317			
Macro Factors, Investor Sentiment and Equity Returns - Indonesia				
CONSTANT	0.5037	0.2136	2.3585	0.0184
ΔSENTIM*OPT	0.4765	0.6166	0.7727	0.4397
ΔSENTIM*TB*OPT	0.0256	0.0269	0.9511	0.3416
ΔSENTIM *IPI*OPT	-0.0042	0.0039	-1.0911	0.2753
ΔSENTIM *TS*OPT	0.0182	0.0689	0.2636	0.7921
ΔSENTIM *PES	-1.3618	0.4623	-2.9457	0.0032
ΔSENTIM *TB*PES	0.0537	0.0188	2.8590	0.0043
ΔSENTIM *IPI*PES	0.0082	0.0035	2.3898	0.0169
ΔSENTIM *TS*PES	0.1940	0.0491	3.9488	0.0001
AR(1)	0.5633	0.0533	10.5719	0.0000
Adj. R^2	0.0512			
D. Watson	2.0009			
Macro Factors, Investor Sentiment and Equity Returns - India				
CONSTANT	0.5160	0.2683	1.9235	0.0545
ΔSENTIM*OPT	2.5154	0.4096	6.1416	0.0000
ΔSENTIM*TB*OPT	-0.1783	0.0681	-2.6175	0.0089
ΔSENTIM *IPI*OPT	-0.0135	0.0030	-4.4958	0.0000
ΔSENTIM *TS*OPT	-0.6127	0.0537	-11.3988	0.0000
ΔSENTIM *PES	-0.4370	0.4477	-0.9761	0.3291
ΔSENTIM *TB*PES	-0.0320	0.0640	-0.4998	0.6172
ΔSENTIM *IPI*PES	0.0083	0.0026	3.1393	0.0017
ΔSENTIM *TS*PES	0.0142	0.0640	0.2216	0.8246
AR(1)	-0.0647	0.0271	-2.3923	0.0168

Adj. R^2	0.0281			
D. Watson	1.9989			
Macro Factors, Investor Sentiment and Equity Returns – China				
CONSTANT	0.3374	0.4523	0.7459	0.4557
ΔSENTIM*OPT	-4.9168	3.3545	-1.4657	0.1428
ΔSENTIM*TB*OPT	0.0565	0.1392	0.4064	0.6845
ΔSENTIM *IPI*OPT	0.0558	0.0366	1.5222	0.1280
ΔSENTIM *TS*OPT	0.0193	0.3676	0.0525	0.9581
ΔSENTIM *PES	-14.1023	1.6769	-8.4096	0.0000
ΔSENTIM *TB*PES	0.1798	0.0879	2.0447	0.0409
ΔSENTIM *IPI*PES	0.1540	0.0176	8.7480	0.0000
ΔSENTIM *TS*PES	1.1326	0.2257	5.0179	0.0000
AR(1)	0.3471	0.0474	7.3234	0.0000
Adj. R^2	0.0746			
D. Watson	1.9981			
Macro Factors, Investor Sentiment and Equity Returns – South Africa				
CONSTANT	0.3937	0.2683	1.9235	0.0545
ΔSENTIM*OPT	-0.2572	0.4096	6.1416	0.0000
ΔSENTIM*TB*OPT	-0.0014	0.0226	-0.0606	0.9517
ΔSENTIM *IPI*OPT	0.0019	0.0072	0.2687	0.7881
ΔSENTIM *TS*OPT	0.0624	0.0215	2.9096	0.0036
ΔSENTIM *PES	-1.2846	0.6217	-2.0662	0.0389
ΔSENTIM *TB*PES	0.0303	0.0162	1.8765	0.0606
ΔSENTIM *IPI*PES	0.0093	0.0054	1.7120	0.0870
ΔSENTIM *TS*PES	-0.0559	0.0173	-3.2256	0.0013
AR(1)	-0.4770	0.0929	-5.1322	0.0000
Adj. R^2	0.0140			
D. Watson	1.9993			
Macro Factors, Investor Sentiment and Equity Returns – Pakistan				
CONSTANT	-0.1408	0.0927	-1.5185	0.1289
ΔSENTIM*OPT	-0.2546	0.3459	-0.7361	0.4617
ΔSENTIM*TB*OPT	-0.0209	0.0142	-1.4734	0.1407
ΔSENTIM *IPI*OPT	0.0103	0.0031	3.3710	0.0008
ΔSENTIM *TS*OPT	0.8158	1.1506	0.7090	0.4783
ΔSENTIM *PES	0.8580	0.2938	2.9207	0.0035
ΔSENTIM *TB*PES	-0.0545	0.0112	-4.8605	0.0000
ΔSENTIM *IPI*PES	0.0022	0.0024	0.9195	0.3579
ΔSENTIM *TS*PES	-0.8927	0.8252	-1.0818	0.2794

AR(1)	0.7347	0.0259	28.3384	0.0000
Adj. R^2	0.1030			
D. Watson	1.9998			
Panel Data Analysis				
CONSTANT	0.0431	0.0168	2.5738	0.0101
ΔSENTIM*OPT	0.6956	0.1041	6.6836	0.0000
ΔSENTIM*TB*OPT	0.3304	0.0681	4.8528	0.0000
ΔSENTIM *IPI*OPT	-0.3149	0.0778	-4.0495	0.0001
ΔSENTIM *TS*OPT	-0.0799	0.0570	-1.4019	0.1610
ΔSENTIM *PES	-0.0079	0.0292	-0.2701	0.7870
ΔSENTIM *TB*PES	0.0546	0.0178	3.0728	0.0021
ΔSENTIM *IPI*PES	-0.0530	0.0210	-2.5231	0.0116
ΔSENTIM *TS*PES	0.0008	0.0148	0.0552	0.9560
AR(1)	0.1191	0.0052	22.7549	0.0000
Adj. R^2	0.0216			
D. Watson	2.0031			

ΔSENTIM*OPT represents optimistic investor sentiment. ΔSENTIM*TB*OPT represents the interaction term of optimistic investor sentiment, and Risk-free rate, ΔSENTIM *IPI*OPT represents the interaction term of optimistic investor sentiment, and industrial production index, ΔSENTIM *TS*OPT represents the interaction term of optimistic investor sentiment and term spread. ΔSENTIM *PES represents pessimistic investor sentiment. ΔSENTIM *TB*PES represents the interaction term of pessimistic investor sentiment and Risk-free rate, ΔSENTIM *IPI*PES represents the interaction term of pessimistic investor sentiment and industrial production index, ΔSENTIM *TS*PES represents the interaction term of optimistic investor sentiment and term spread.

Table 4.11 reveals that when studied without involving the macro factors, bullish investor sentiment has a significant positive effect on equity returns only in Brazil and India and a significant negative in South Africa. When the effect of bullish investor sentiment is analyzed in combination with the Risk-free rate, it has a significant negative effect in Russia and India; when it is combined with the industrial production index, it has a significant positive effect in Brazil and a negative in India when combined with Term Spread, it has a positive effect in South Africa and Pakistan and negative in Brazil, Russia, and India.

The effect of bearish investor sentiment, when investigated in isolation from other macro factors, has a significant negative effect on returns in Indonesia, China, and

South Africa. The effect of bearish investor sentiment, in combination with the Risk-free rate, is significantly positive in Russia, Indonesia, China, South Africa, and Pakistan. When studied in combination with the industrial production index, this effect has a significant positive effect in Indonesia, India, China, and South Africa and a negative in Pakistan. When studied in combination with Term Spread, it has a positive effect in Indonesia and China and a negative in South Africa.

At an aggregate level, when the effect of bullish investor sentiment on return is studied in isolation from other macroeconomic factors, it significantly affects returns. When the effect of bullish investor sentiment is analyzed in combination with the Risk-free rate, it has a significant positive effect, and when combined with the industrial production index, it has a significant negative effect. It becomes insignificant when combined with Term Spread. Bearish investor sentiment has an insignificant effect on returns when analyzed in isolation. The combination of bearish investor sentiment with a Risk-free rate has a significant positive effect, and the combination with the industrial production index has a significant negative effect. It becomes insignificant when investigated in combination with Term Spread.

The negative effect of the Risk-free rate on the relation of bullish sentiment and returns in Russia and India is due to the preference of investors to invest in safer assets such as bonds rather than stocks, which leads to lower equity returns. The positive effect of the Risk-free rate on the relation of bearish sentiment and returns in Russia, Indonesia, China, South Africa, and Pakistan is because the investors prefer to invest in stocks rather than other safer assets, which amplifies the positive effect of bearish sentiment on equity returns.

In countries where the industrial sector is a significant contributor to the economy, such as Brazil, the Industrial Production Index amplifies the positive effect of bullish sentiment on equity returns. However, in India, where the industrial sector is relatively small, the effect of bullish sentiment on equity returns is less pronounced. The positive effect of the Industrial Production Index in Indonesia, India, China, and South Africa, indicates that the economy in these countries is growing, leading to higher equity returns. Therefore, in the presence of a high IPI, the effect of bearish investor sentiment on equity returns is stronger.

A positive effect of the term spread on the relation between optimistic investor sentiment and returns observed in South Africa and Pakistan indicates that these economies are stronger and generate higher equity returns. The negative term spread in Brazil, Russia, and India indicates a weak economy in these countries that generate lower equity returns. Similarly, a positive effect of the term spread on the relation between pessimistic investor sentiment and returns observed in Indonesia and China witnesses the strength of the economies of these countries. A negative term spread in South Africa witnesses its weak economy. Therefore, in the presence of a positive term spread, the effect of optimistic or pessimistic investor sentiment on equity returns is stronger, while in the presence of a negative term spread, the effect becomes weaker.

4.12 COVID-19, Investor Sentiment and Equity Returns

To analyze the effect of COVID-19 on the relationship of investor sentiment with equity returns at the country level, the Auto Regressive model is applied, and at the aggregate level Dynamic Panel Fixed Effect model is applied. Table 4.12 reports the relation of bullish and bearish investor sentiment with equity returns during COVID-19.

Table 4.12: Relation of Bullish and Bearish Investor Sentiment with Equity Returns during COVID-19

COVID-19, Optimistic and Pessimistic Investor Sentiment and Equity Returns – Brazil				
Variable	**Coefficient**	**Std. Error**	**T-statistic**	**Prob.**
CONSTANT	1.5669	0.0617	25.4036	0.0000
COVID-19	-1.2591	0.1761	-7.1504	0.0000
ΔSENTIM*OPT	0.0808	0.0409	1.9752	0.0483
ΔSENTIM *PES	-0.0523	0.0409	-1.2771	0.2016
COVID-19 * ΔSENTIM *OPT	0.4159	2.3525	0.1768	0.8597
COVID-19 * ΔSENTIM *PES	-0.0488	2.5921	-0.0188	0.9850
AR(1)	0.0204	0.0130	1.5727	0.1159
Adj. R^2	0.1196			

D. Watson	1.7570			
COVID-19, Optimistic and Pessimistic Investor Sentiment and Equity Returns – Russia				
CONSTANT	0.0617	0.0358	1.7209	0.0853
COVID-19	0.0120	0.1426	0.0841	0.9329
ΔSENTIM*OPT	0.3658	0.1338	2.7329	0.0063
ΔSENTIM *PES	-0.2777	0.0514	-5.4003	0.0000
COVID-19 * ΔSENTIM *OPT	-0.3540	0.2445	-1.4481	0.1476
COVID-19 * ΔSENTIM *PES	0.5224	0.1970	2.6513	0.0080
AR(1)	0.1528	0.0061	24.7329	0.0000
Adj. R^2	0.0253			
D. Watson	1.9966			
COVID-19, Optimistic and Pessimistic Investor Sentiment and Equity Returns – Indonesia				
CONSTANT	0.0283	0.0143	1.9799	0.0478
COVID-19	-0.0449	0.0634	-0.7082	0.4788
ΔSENTIM*OPT	0.2067	0.0412	5.0169	0.0000
ΔSENTIM *PES	0.2917	0.0481	6.0654	0.0000
COVID-19 * ΔSENTIM *OPT	0.4565	0.1518	3.0079	0.0026
COVID-19 * ΔSENTIM *PES	0.2556	0.1540	1.6591	0.0972
AR(1)	0.6755	0.0763	8.8503	0.0000
Adj. R^2	0.0490			
D. Watson	2.0040			
COVID-19, Optimistic and Pessimistic Investor Sentiment and Equity Returns – India				
CONSTANT	0.0055	0.0254	0.2175	0.8278
COVID-19	0.3165	0.1493	2.1202	0.0340
ΔSENTIM*OPT	-0.0264	0.0626	-0.4211	0.6737
ΔSENTIM *PES	-0.2712	0.0670	-4.0473	0.0001
COVID-19 * ΔSENTIM *OPT	-0.1490	0.2748	-0.5421	0.5878
COVID-19 * ΔSENTIM *PES	0.8376	0.2718	3.0819	0.0021
AR(1)	0.1319	0.0138	9.5728	0.0000
Adj. R^2	0.0203			
D. Watson	2.0017			
COVID-19, Optimistic and Pessimistic Investor Sentiment and Equity Returns – China				
CONSTANT	-0.1188	0.0305	-3.8997	0.0001
COVID-19	-0.1515	0.1143	-1.3259	0.1849

ΔSENTIM*OPT	1.7767	0.2112	8.4136	0.0000
ΔSENTIM *PES	0.0368	0.1876	0.1962	0.8445
COVID-19 * ΔSENTIM *OPT	0.3920	0.6383	0.6141	0.5392
COVID-19 * ΔSENTIM *PES	-0.8806	0.3946	-2.2316	0.0257
AR(1)	0.0414	0.0220	1.8847	0.0595
Adj. R^2	0.0453			
D. Watson	2.0179			
COVID-19, Optimistic and Pessimistic Investor Sentiment and Equity Returns – South Africa				
CONSTANT	0.0308	0.0352	0.8742	0.3821
COVID-19	0.4689	0.1204	3.8931	0.0001
ΔSENTIM*OPT	-0.0239	0.0297	-0.8053	0.4207
ΔSENTIM *PES	-0.0282	0.0402	-0.7026	0.4823
COVID-19 * ΔSENTIM *OPT	-0.6030	0.0664	-9.0838	0.0000
COVID-19 * ΔSENTIM *PES	0.4092	0.0685	5.9747	0.0000
AR(1)	-0.5862	0.0483	-12.1319	0.0000
Adj. R^2	0.0167			
D. Watson	1.9984			
COVID-19, Optimistic and Pessimistic Investor Sentiment and Equity Returns - Pakistan				
CONSTANT	0.0437	0.0291	1.5037	0.1327
COVID-19	-0.1579	0.1201	-1.3141	0.1889
ΔSENTIM*OPT	0.6156	0.0963	6.3929	0.0000
ΔSENTIM *PES	0.5702	0.0740	7.7042	0.0000
COVID-19 * ΔSENTIM *OPT	0.4583	0.3525	1.3000	0.1937
COVID-19 * ΔSENTIM *PES	-0.5943	0.2716	-2.1883	0.0287
AR(1)	0.1682	0.0245	6.8584	0.0000
Adj. R^2	0.0962			
D. Watson	0.0962			
Panel Data Analysis				
CONSTANT	0.0258	0.0092	2.8048	0.0050
COVID-19	0.0695	0.0451	1.5430	0.1228
ΔSENTIM*OPT	0.1467	0.0221	6.6428	0.0000
ΔSENTIM *PES	0.0423	0.0223	1.8994	0.0575
COVID-19 * ΔSENTIM *OPT	-0.0888	0.0929	-0.9562	0.3390
COVID-19 * ΔSENTIM *PES	0.1605	0.0873	1.8388	0.0660
AR(1)	0.1134	0.0052	21.6429	0.0000
Adj. R^2	0.0156			

D. Watson	2.0006

ΔSENTM *OPT is Optimistic investor sentiment, ΔSENTIM *PES is pessimistic investor sentiment, COVID-19 is epidemic, COVID-19 *ΔSENTIM*OPT is the interaction term of COVID-19 and Optimistic investor sentiment and AR is Auto Regressive term.

Table 4.12 reveals that, when COVID-19 is not considered, optimistic investor sentiment in Brazil, Russia, Indonesia, China, and Pakistan significantly affects equity returns. However, when the effect of optimistic investor sentiment is analyzed in combination with the effect of COVID-19, it becomes insignificant in all the countries except Indonesia and South Africa. The insignificant effect is due to the reason that optimistic investors in these markets, being over-confident, overlook bad news and thus have no impact on the returns during a pandemic. In Indonesia, COVID-19 has strengthened the relationship between investor sentiment and returns, whereas in South Africa has weakened the relationship. This observation is associated with the awareness and responsiveness of investors toward bad news in the market.

Pessimistic investor sentiment, when studied excluding the effect of COVID-19, shows a significant effect on returns in Russia, Indonesia, India, and Pakistan; however, when it is observed, inclusive of the effect of COVID-19, it is significant in all of the selected countries except Brazil where it is insignificant. The effect of COVID-19 on the relationship of pessimistic investor sentiment with returns is significantly positive in the markets of Russia, Indonesia, India, and South Africa. This relationship is strengthened with the emergence of the epidemic, which is associated with the sensitivity of pessimistic investors to bad news in the market. The epidemic's effect on the relationship of pessimistic investor sentiment with returns is significantly negative in China and South Africa. It happens because of mispricing created by pessimistic investors due to their uncertainty about the market's future, resulting in lower returns being corrected.

At the aggregate level, the sentiment of pessimistic and optimistic investors has a significant positive effect on equity returns when studied, excluding the effect of COVID-19. The effect of optimistic investor sentiment, when studied jointly with the effect of COVID-19, becomes insignificant. These results are because optimistic investors give more importance to good news and ignore bad news without affecting the market functioning. The significant positive effect of COVID-19 on the relationship between equity returns and pessimistic investor sentiment indicates that COVID has strengthened the relationship between the two. This is due to over emphasis of pessimistic investors on bad news in the market. It is deduced from the above results that different levels of investor sentiment significantly impact the market returns concurrently and in the short term, even in the presence of different macroeconomic and risk factors. The results indicate that stock markets are influenced by both rational as well as irrational investors. The irrational investors take investment decisions based on their sentiments, and are responsible for deviation of prices, in the market, from their intrinsic value. As compared to developed stock markets, the fluctuation of prices is more common in emerging stock markets, because these markets have a larger number of irrational investors and are more susceptible to investor sentiments.

Chapter 5

Conclusion and Recommendations

This chapter includes a summary of the main findings, recommendations, limitations, and future directions of the study.

5.1 Findings of the Study

When traditional finance theories, which claimed that investors are rational in trading, and keep the market prices fair without allowing abnormal gains, failed to fully explain fluctuations in asset prices observed in the markets, then behavioral finance tried to explain this phenomenon based on human psychology and theorized that investors are irrational in trading that is why prices in the market fluctuate that leads to abnormal returns. This diverse behavior of investors is attributed to investor sentiment. Investor sentiment has been a topic of research in the studies of market behaviors, and a lot of research has been carried out in this regard; however, the results need to be more uniform. In literature, controversies exist regarding the nature, direction, and magnitude of equity returns and their role in the market risk in the macroeconomic environment. Therefore, the present study is carried out to explore the effect of different levels of investor sentiment on current and future equity returns at different time horizons in the presence of market volatility and macro factors. In this study, secondary data of representative indices of Brazil, Russia, Indonesia, India, China, South Africa, and Pakistan (BRIICSP) is collected for a period from 2001 to 2020. Daily share prices are converted into returns, and data on macroeconomic variables are converted from monthly to daily basis. Principal Component Analysis is applied to construct Investor Sentiment Index by taking Trading Volume and Turnover Ratio as proxies. The impact of investor sentiment on returns in different contexts is calculated for each country separately and then grouped for a panel study. Auto-Regressive Model/Auto Regressive Moving Average Model are applied for country-level analysis, and Dynamic Panel Model/ Dynamic Fixed Effect Model is applied for group-level analysis. The data is analyzed and the results are presented in tabulated form following the study's objectives, and the contents of the table are elaborated in textual form.

In linear and nonlinear terms, investor sentiment has a significant positive impact on same-day returns in all the countries under study except India and South Africa, where the relationship is significant only in linear terms. At the group level, investor sentiment positively impacts contemporaneous market returns linearly. Investor sentiment significantly impacts current market returns, and this influence is continued in the short run in most of the sample countries. However, the impact of sentiment is not much pronounced in the longer run.

When investor sentiment is categorized into optimistic and pessimistic, both optimistic and pessimistic states of investor sentiment, have a significant effect on equity returns in all countries except South Africa, where only an optimistic state significantly impacts returns. The relationship is non-linear and convex in nature. The optimistic investor sentiment and the Pessimistic investor sentiment have respectively positive and negative impacts on equity returns; however, in both cases, it reverts at further higher levels. When investor sentiment is decomposed into moderate, extremely optimistic, and extremely pessimistic levels, at a moderate level, investor sentiment shows a significant effect on returns, an extremely optimistic level shows a significant effect except for Brazil and South Africa, and an extremely pessimistic level shows significant effect except for Brazil.

When the role of investor sentiment is studied in the context of risk regarding the nature of the relationship, optimistic and pessimistic investor sentiment increases the volatility in Russia, China, South Africa, and Pakistan. It decreases the volatility in Brazil, India, and Indonesia in linear settings. In nonlinear terms, optimistic investor sentiment increases the volatility in Brazil, Russia, Indonesia, India, and China and decreases the volatility in South Africa. At the group level, optimistic and pessimistic investor sentiment negatively relates to volatility. In nonlinear settings, bullish investor sentiment has a positive relation with volatility, and bearish investor sentiment has a negative relation with volatility.

Market risk is measured using 4 metrics that are VaR-95, VaR-99, CVaR-95, and CVaR-99, and analyzed its impact on the returns during high and low sentiment levels. High investor sentiment has a negative effect on the relationship of VaR-95 and VaR-99 with equity returns in Russia, Indonesia, China, and Pakistan and positive in Brazil, India, and South Africa at the country and group level. Low investor sentiment negatively affects the relationship of Var-95 and VaR-99 with equity returns in all the countries individually and at the panel level. Optimistic investor sentiment has a significant positive effect on the relationship of CVaR-95 and returns in Brazil and South Africa; a negative effect in Indonesia, China, and Pakistan; and an insignificant effect in Russia and India when taken at a country level and a negative effect is observed at the panel level. Pessimistic investor sentiment has a significant negative effect on the relationship between CVaR-95 and equity returns in all the selected countries at individual and aggregate levels. Optimistic investor sentiment has a significant positive effect on the relationship between CVaR-99 and equity returns in Brazil and South Africa and a significant negative effect in Indonesia, India, China, and Pakistan. Pessimistic investor sentiment has a significant positive effect on the relationship between risk and equity returns in Indonesia, significantly negative in all the countries except China. At the aggregate level, optimistic and pessimistic investor sentiment has a negative effect.

When the effect of investor sentiment is analyzed in the presence of change in macroeconomic variables, optimistic investor sentiment has an insignificant effect on equity returns in all the countries except Indonesia and South Africa during COVID-19. In contrast, the pessimistic investor significantly affects returns in all selected countries except Brazil. At the group level, optimistic investor sentiment shows an insignificant effect, whereas pessimistic investor sentiment significantly affects returns during the epidemic. When the effect of bullish investor sentiment on equity returns is considered, in the presence of a risk-free rate, it has a significant negative effect in Russia and India; in the presence of industrial production index, it has a positive effect in Brazil and a negative effect in India; and in the presence of term spread, it has a positive effect in South Africa and Pakistan and negative in Brazil, Russia, and India. When the effect of bearish investor sentiment on returns is considered in the presence of a risk-free rate, it has a significant positive effect in all the countries except Brazil and India; in the presence of the industrial production index, it has a significant positive effect in Indonesia, India, China, and South Africa and negative in Pakistan; in the presence of term spread, it has a positive effect in Indonesia and China and negative in South Africa. At the aggregate level, bullish and bearish investor sentiment positively affects returns in the presence of a risk-free rate, negative in the presence of industrial production index, and insignificant in the presence of term spread.

It is concluded that different levels of investor sentiment significantly impact the market returns concurrently and in the short term, even in the presence of different macroeconomic and risk factors.

5.2 Future Recommendations

- The findings of the investigation will supplement the body of knowledge and helpful for researchers to understand the market concepts in more unified manner. They will be able to understand the relationship among various variables with more clarity. They will be able to expand the research, based on the findings of this study.

- This study will help policy makers, company managers, and stock market administrators to understand the different levels of investor sentiment that are key drivers for price fluctuations in the stock market and will be able to devise strategies to manage the stock fluctuations in a better way.

- The results of this study help investors to better understand the market trends under the influence of sentiments.

- It is also helpful for portfolio managers and risk professionals to make systematic predictions and devise strategies for asset allocation, portfolio restructuring, and risk management.
- It is also helpful for policymakers to make systematic predictions and devise appropriate strategies to move the market toward efficiency.
- The results of this study are helpful for researchers who tend to extend their studies with variant proxies, markets, and time limits to reach a generalized conclusion.

5.3 Specific Recommendations

- The nutshell of the study is that investor sentiment is a predictor of equity market returns and plays a significant role in creating volatility, therefore, sentiments should be priced.
- Investor Sentiment Dynamics show a divergent impact in the emerging equity markets concurrently and in the short term, even in the presence of different macroeconomic and risk factors. So, stakeholders should give importance to the investors' sentiments while making investment decisions.

5.4 Limitations and Future Directions of the Study

- Investor sentiment is a subjective measure, and there is no well-defined method to measure the sentiment of the investors quantitatively, therefore, proxies already in use are employed here to quantify the sentiment. New tools of measurement for the quantification of the sentiment may be developed.
- Sentiment, a trait of human behavior, cannot be quantitatively measured even through a well-defined and unified tool; thus, many proxies are used to quantify it. Similarly, the traits dependent on human sentiment are likely to

show different results under different conditions. Therefore, there is a need to utilize many more measures to get more reliable results.

- Changes in investor sentiment are very rapid, and it is not possible to study them at a specific moment in time, therefore, synchronous studies are needed to carry out.

- There are many other factors influencing investor sentiment which are not part of this study, therefore such factors may be included in future studies.

- The volume of trading activities can be relatively low in emerging markets as compared to developed markets. Resultantly, the conclusions drawn regarding the effect of investor sentiment are subject to the question of accuracy, therefore, measures other than the volume of trading may be employed.

- Low values of Adjusted R-square observed here and also by Kim and Ryu (2020) and Chang et al. (2017) show that market returns are not under the influence of investor sentiment only; other factors also have a compound effect on them, such factors may be part of the future studies.

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