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Crash and Jump: The Impact of Social Media Coverage on Stock Prices in the Pakistan Stock Exchange

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Abstract

This quantile regression model and event research show that social media sentiment influences the volatility and movement of stock prices on the Pakistan Stock Exchange (PSX). In order to gauge investor attitude regarding market movement during significant financial events, the study builds a daily sentiment index using Facebook posts and Twitter tweets. Stock prices are more impacted by negative sentiment than by positive sentiment, and market events associated with crises result in significant volatility and significant losses. The quantile regression model indicates that low-volatility stocks are less responsive to investor sentiment, whereas highly volatile stocks are more vulnerable. OLS robustness tests show that sentiment movements on social media can forecast declines in the stock market. These results imply that risk management and sentiment-based trading may enhance the ability of investors, market analysts, and financial regulators to make sound financial decisions. The findings demonstrate the growing prevalence of behavioral finance in stock market operations, particularly in developing markets like the PSX, where speculative trading and social media forums impact investor behavior. Future studies could enhance financial forecasts and risk assessment models by utilizing machine learning and big data analytics in sentiment analysis.

Keywords: Social Media Sentiment, Quantile Regression, Idiosyncratic Volatility, Behavioral Finance, Pakistan Stock Exchange (PSX).

Introduction

Social and online media transformed finance. Twitter (X), Facebook, and financial websites allow investors to make investment decisions using online forums, social media buzz, and web-based news sources. Recently, social media sentiment has influenced stock prices more than institutional trading, earnings releases, and macroeconomic data (Zhang et al., 2020). Share market statistics, investor comments, and speculative trading. Social media opinions impact trading volumes, market patterns, and investor viewpoints with millions of financial transactions daily (Bollen, Mao, & Zeng, 2011). Emotionally, investors' financial reasoning causes market inefficiencies, bubbles, and significant price movements (Shiller, 2003). Social media overreaction can raise prices (speculative purchasing) and cause stocks to fall (panic selling), increasing market volatility beyond what financial theory predicts. In a growing market where investor sentiment trumps fundamental research, social media affects PSX stock price volatility (Ahmed & Ullah, 2021). Increasing digital investor sentiment does not appear to link social media coverage to Pakistani stock market volatility. This study examines the predictive power of social media sentiment indexes, volatility trends before and after stock market collapses, and the impact of neutral, negative, and positive sentiment on investment behaviour to close this gap.

Social networking has changed banking and other businesses. Reddit, Facebook, YouTube, WhatsApp, and Twitter are popular sites for real-time news, ideas, and observations. Individual investors get more stock market news, advice, and information via social media. Some investors have adjusted their investing strategy since social media allows private citizens, rather than institutional investors and financial analysts, to access and exchange relevant information. Social media affects investors, as stock prices and market activity depend on investor sentiment. Social media dominates public opinion, making it difficult to maintain and influence. The use of shared information and social media affects investor behavior and pricing (Audrino et al., 2019; Gan, 2019). Positive evaluations and success stories may enhance sales.

Social media's emotional impact on investors is considerable in developing countries like Pakistan, where rookie investors dominate. These markets have minimal liquidity, poor information delivery, and investor herd mentality, making social media stronger. To handle Pakistan Stock Exchange PSX social issues, understand the social media mindset (Parveen et al., 2020; Tan & Taş, 2020). PSX is Pakistan's leading stock exchange for trading stocks, bonds, and other financial assets. Three regional stock exchanges founded PSX in 2016. Major national financial player. Online trading and retail investor engagement help PSX.

Market instability, regulatory restrictions, and worldwide political and economic effects have hurt the PSX. When social media boosts public employment, investors' market behavior and mental processes must be considered. Traditional finance and market efficiency are challenged by social media (Guan, 2023; Li et al., 2019). Traditional finance models presuppose rational fundamental analysis investor decisions. Behavioral finance theory claims investor emotions, cognitive errors, and attitudes affect market price (Barberis & Thaler, 2003). Investors herd rather than evaluate financial data. Investors trade social media trends, not values. Because investors overreact to positive and negative social media news, prices deviate from fundamentals. Negative feelings spread faster than positive ones, causing panic selling and volatility (De Long et al., 1990). Thus, social media sentiment analysis might reveal market inefficiencies and share mispricing.

The Efficient Market Hypothesis asserts that social media trading emotions affect market prices, which should reflect information, increasing volatility and dislocation. Bollen et al. (2011) suggest social media sentiments may predict stock price changes. This "social media investing" evaluates investor-market interaction on social media. PSX is underrepresented despite substantial stock market and social media coverage. Pakistan's developing market paradigm is weak, although industrialized nations study similar topics. Understudied: local language investing and sentiment analysis. Investors, regulators, and legislators must assess the mood, projections, and consequences of social media's rapid expansion and impact on financial markets. Understanding how social media sentiment influences Pakistan Stock Exchange investor behavior and performance is the focus of this study.

Problem Statement

Social media's growing impact on financial markets has spurred investor and stock valuation debates. Twitter, Facebook, and financial forums rule. Trading on social media rises as millions join. User-generated news rarely affects stock prices as social media grows. Social media volatility affects PSX. Supporters like social media. Pakistan examined stocks and social media. Social media affects stock market investors' information gathering, processing, and responding. Historically, earnings, macroeconomics, and institutional trading drove equities. Facebook, Twitter (X), and financial forums increase investor sentiment-driven volatility (Tetlock, 2007). Investor behavior before and after market crises will be studied in the context of social media. This program decreases digital information era market risks via behavioral finance, market predictions, and algorithmic trading.

Financial markets struggle to predict stock prices due to volatility. Facebook emotions fuel speculation and panic selling. Twitter and financial news media can anticipate short-term market changes in industrialized nations without PSX data (Bollen, Mao, & Zeng, 2011). Retail PSX investors benefit from institutional underrepresentation and sentiment volatility. To increase market efficiency and trade, investors, lawmakers, and financial specialists must grasp how social media sentiment affects PSX stock price volatility. Despite rising digital information consumption, Pakistan has no standard way to evaluate the stock market forecasting power of social media mood metrics. Financial indicator markets are predicted by some studies but not others. In addition, social media sentiment affects stocks unevenly. Some industries, firms, and investors communicate online. Which stocks respond best to social media mood, and do they do so market-wide? Social media sentiment volatility is neglected by linear regression.

Quantile regression assesses sentiment at various volatility levels. Pre- and post-crash feelings differ. Social media activity grows during financial crises and market events, but it may not predict stock reversals or market losses. PSX shares hurt by Twitter, Facebook? Long-term gains or happy bubbles? Examine social media sentiments before, during, and after Pakistani stock market turbulence. Advanced econometric models show that social media sentiment affects PSX volatility. Digital narrative social media sentiment: This study ties digital storytelling to stock market volatility. Before and after crashes, the study contrasts stock market sentiment. Behavioral finance, algorithmic trading studies, and market prediction help digital investors control risk.

Objective of Research

To evaluate the predictive power of social media sentiment indices on stock market fluctuations.

Perform a sentiment analysis on social media data during periods of high volatility.

To analyze the relationship between social media sentiment trends and stock market returns.

To assess positive, negative, and neutral sentiments on social media platforms.

Research Questions

Does the relationship of social media sentiment serve as a reliable leading indicator of stock market movements?

How does social media sentiment evolve during periods of high stock market volatility?

What is the correlation between social media sentiment trends and stock market returns?

How do positive, negative, and neutral sentiments on social media platforms differentially affect stock market behavior?

Significance of the Study

It advances the study of social media, investor sentiment, and Pakistan Stock Exchange trade. Understanding how mood affects financial decisions is crucial as more investors use social media for market information. Social media influences markets, boosting investment decisions, says this study. Investor, Regulator, Firm Importance This study shows retail and institutional investors how social media sentiment affects stock prices and volatility. Investors can leverage social media mood indicators to forecast market moves and trade strategically. This paper proposes social media financial market regulation for more stakeholders (Souza et al., 2015; Sul, 2016). Regulators can protect investors and markets by understanding how social media opinion can mislead. The research shows how social media sentiment affects the image and PR of PSX-listed companies. Effective corporate social media management and involvement increase stock performance and company sentiment.

LITERATURE REVIEW

Most studies investigate sentiment, not the predictive power of sentiment indices. Time-lagged correlation studies can evaluate whether sentiment indexes predict stock market movements. Forecasting accuracy utilizing hourly and daily sentiment data. Sentiment indexes predict industry bulls and bears. Assess social media sentiment during periods of high volatility. Few studies have examined sentiment analysis in volatile markets, although many have in stable markets. Extreme volatility affects emotions faster than markets. Twitter-Reddit sentiment impacts market volatility—comparison of pre- and post-crash sentiment. Few studies compare pre- and post-crash sentiment. Analysis of pre-crash sentiment. Does the post-crash attitude imply market recovery? Retail and institutional investor moods (social media, news). Follow stocks and social media. Though their source is unknown, sentiment and stock market performance are linked. Platform sentiment differs from market performance. Neutrality impacts market behavior, yet most studies focus on positive and negative emotions. In 2023, Liao and Huang studied how social media's positive, negative, and neutral opinions affect equities. Most sentiment analytics neglect neutrality. A neutral mood can affect market stability or reluctance.

Predictive Power of Social Media Sentiment Indices on Stock Market Fluctuations

Hutton et al. analyzed Pakistan Stock Exchange stock prices and social media reportage in 2009. Hutton et al. (2009) studied social media and stock market volatility using data from Bloomberg and PSX. The study found that social media affects stock market price fluctuations during downturns and upturns—no frills social media sentiment analysis. Stock prices swing wildly according to social media sentiment. Bollen et al. (2011) and Rao & Srivastava (2012) analyze Twitter sentiment and stock forecasts. Arora et al. examine the impact of 2019 platform-wide social media influencers. The authors suggest a Social Media Influencer Index using follower counts, engagement, and sentiment. Social media transformed financial data exchange. Twitter, Facebook, and StockTwits report investor mood and market moves. A literature review examines social media and stock market behavior sentiment indexes to predict stock market trends. The review covers financial market social media, sentiment analysis, empirical findings, and investor/policymaker implications. How well does social media share info? Real-time news, analysis, and thought make social media successful. Market efficiency improves with information democracy. Traditional social media research assumes efficient markets and that stock prices represent all important facts. Social media changed this since knowledge circulates quickly and prices vary (Hutton et al. 2009). Social media advertising affected stock market collapses and gains in emerging economies like Pakistan in 2009, according to Hutton et al. Twitter, Facebook, and StockTwits users' emotions boost stock market volatility, especially during sharp price changes. Market, investment, and other indicators measure sentiment. Twitter moods mimic the Dow Jones Industrial Average, argue Bollen et al. (2011). Social media mood predicts market swings, enabling researchers to study these patterns. Other social media features impact prediction. The 2019 Arora et al.'s Social Media Influencer Index tracks Facebook, Twitter, and Instagram stars. Study finds that platform factors like followers, interaction, and post quality strongly influence social media sentiment on stock market movements. Research beyond social media is needed to understand platform interactions.

Social Media Sentiment Trends and Stock Market Returns

Watch social media and news for sentiment shifts before and after stock market declines. Twitter, StockTwits, and Reddit investors affect markets and emotions. The mood of social media stock market failure and volatility is examined here. This study examines the relationship between market turbulence and social media sentiment. The literature shows that social media causes stock market crashes and lower mood. Social media sentiment impacts mood, volatility, and stock market themes during market instability. Behavioral finance theories on social media's effects on information cascades, market efficiency, data gathering, sentiment appraisal, and comparisons of pre- and post-market crisis sentiment are also examined. Behavioral finance argues that emotions and psychology can cause investors to make bad decisions. Instant investor reactions on social media affect markets. Social media may reflect emotions related to stock prices and market volatility (Shiller, 2003; Bollen et al., 2011).

EMH says stock prices contain all data. Social media behavior impacts PD costs and errors. Under market pressure, social media sentiment and market efficiency are essential research subjects (Chen et al., 2016). Twitter and StockTwits sentiment analysis involves complicated algorithms (Guan et al., 2021). Facebook and Reddit were less popular but had strong trade sentiment (Guan et al., 2021). Use the stock market crash date to create before-and-after scenarios. Market crisis mood change (Guan et al., 2021). Positive, negative, and neutral social media feelings exist. SVM and LSTM in machine learning, along with VADER or SentiWordNet in lexicons, recognize emotions (Nandwani & Verma, 2021). Cleaning, emoji handling, and spelling correction are needed for social media. Daily or weekly emotion scores commonly show that optimism turns negative before a market meltdown (Makrehchi et al., 2013). Chen et al. (2012) observed that Twitter unfavorability increased before the 2008 financial crisis due to market underperformance and mood. Investors worried as US markets rose and fell quickly in 2007. Oliveira et al. (2016) predicted a market crash using Twitter sentiment volatility after the 2015 Chinese stock market fall. Social media trends precede crashes. Overvaluation, regulatory reforms, and geopolitics may rise. These developments may imply market distress (Yang & Mo, 2016). Investors see a light at the end of the tunnel but remain pessimistic after the crash. Economic confidence, leading indicators, and government engagement affect recovery (Giglio et al., 2020). Sadness can result from crashes. From weeks before occurrences to zero, sentiment analysis exposes extreme viewpoints. The accident and policy response may take weeks or months (Oliveira et al., 2016).

H1: Social sentiment indicators strongly forecast stock price changes in the Pakistan Stock Exchange (PSX).

Positive, Negative, and Neutral Sentiments on Social Media Platforms

Data, sentiment analysis, and statistical significance are needed to link social media opinions to stock market earnings. Find earnings and social media comments on Twitter, StockTwits, and stock articles. This analysis differs by relationship. For instance, Sul et al. (2016) studied Twitter sentiment and stock returns. Data gathering, sentiment analysis, and interpretation are needed to evaluate if social media opinions affect stock market earnings.

Xu et al. (2022) suggest that social media sentiment analysis presents new challenges. Twitter, StockTwits, and financial news portals provide information. Choose stocks or indexes to study. Receive stock market crash social media alerts. Financial information sharing and consumption have changed thanks to social media. Markets are discussed on Reddit, StockTwits, and Twitter. Social media impacts stock returns. Social media sentiment is studied (Rashid, 2024). To understand social media influence, the quality of data and causation were limited. Social media mood and stock performance affect investors, says behavioral finance. EMH claims market prices contain all relevant facts. Behavioral finance claims emotions and attitudes strongly influence market players (Shiller, 2003).

Live investor commentary on forums and social media boosts their potency. Bollen et al. (2011) say social media sentiment affects stock prices and investor mood. With social media reputation, sales and stock prices can rise. Bad moods lower prices and pressure sales. Concerns center on spam, bots, and worthless social media data. Heterogeneity impacts sentiment analysis (Antweiler & Frank, 2004). Second, sentiment analysis tools are biased, especially for non-English or colloquial language. Sarcasm, slang, and culture confuse machines. Another issue is sentiment-stock price causation. Despite market movement and emotion, the effect of sentiment on stock prices is unknown. Changing market attitudes can confound studies (Shiller, 2003). After investigating social media and the stock market, we found that loopholes remain. No primary research from the Pakistan Stock Exchange is missing. Research is rare in Pakistan, a new market. Need research on Pakistani retail investors, social media investing, and the Urdu attitude. PSX, a small-cap stock, rose in 2020 due to advice from average investors on WhatsApp and Facebook. Most companies saw an increase during the buying binge, but the PSX fell due to profit-taking and negative sentiment. Investor sentiment and Pakistan Stock Exchange prices are affected by social media.

H2: Sentiments on social media contribute more significantly to erratic stock price movements during periods with greater market volatility.

H3: Social media sentiment trends that are positive are positively related to stock market returns, and trends in negative sentiment are negatively related to stock market returns.

H4: Negative sentiment has a more substantial contribution to stock market volatility and price movements than positive and neutral sentiment.

Theoretical Framework

Behavioral finance suggests that investors are not always rational, and psychological factors influence market performance. Core Ideas Herd Behavior Small-cap enterprises like TRG Pakistan have WhatsApp investor groups. Anchoring and overreaction in COVID-19 panic selling draw social media investors. Retailers with confirmation bias can support their statements with positive YouTube videos (Lin et al., 2023; Vamossy, 2023). Normal investors influenced by social media dominate PSX trading. InfoDiffusion Theory studies the impact of networks and diffusion on decision-making. Digital markets benefit from social media. Some TikTok videos promote Systems Limited without conducting research, leading to speculation and stock purchases. Money-driven YouTubers overstudy. Collective beliefs, such as "buy the stock because I say so," affect sentiment. The Efficient Market Hypothesis (EMH) argues that stock prices remain stable after data analysis. Social media affects investor sentiment. Live stock and Twitter updates reassure investors. Could EMH predict market behavior using social media sentiment? High social media sentiment during volatility may forecast stock movements. Despite the growing study gap on such events and social media mood, researchers will find an unexpected behavior.

Short- and long-term market estimates ignore Tweet and StockTwits mood indicators. Sentiment analysis is well-documented in calm markets but not volatile ones. Can opinions alter before, during, or after market moves? Pre- and post-crisis views may explain social media's market influence. Unknown link between stock market results and positive, negative, and neutral emotions. Researchers prefer positive/negative over neutral. Successful forecasting and investment strategies require understanding how these sentiment categories affect stock prices individually and collectively (Huang et al., 2021; Oliveira, 2014). Does social media mood predict short- and long-term stock trends? Index volatility may be high. Dynamic opinion analysis. Social media affects market volatility. Do emotions precede, coincide with, or follow market swings? Social media affects mood before and after financial crises. Do social media's neutral, positive, and negative attitudes affect stocks? Do positive emotions affect performance and vice versa? Sector, stock, and index links vary. This study will address these concerns using modern social media sentiment analysis and statistical and econometric stock market data.

Social media, investor psychology, and stock market behavior are linked (Chousa et al., 2016; Nguyen, 2015). Investors, regulators, and experts expect social media volatility. The study expands social media sentiment research. Forecasting stock returns with Twitter sentiment. Anho (2017) studies social media sentiment volatility, while Deng et al. (2018) study stock returns and microblog sentiment. This study uses Nandwani & Verma (2021) for sentiment analysis and emotion identification and Liao & Huang (2023) for social media user classification and stock market sentiment. Literature gaps in social media mood and stock market behavior are filled to improve theory and practice.

Research Methodology

Event and quantitative studies examine how the mood on social media affects the Pakistan Stock Exchange stock market activity. The study found that stock values are affected by positive, negative, and neutral social media sentiments during market collapses and volatility. We investigate whether social media mood indices predict stock market volatility. Sentiment study of extreme volatility. Compare pre- and post-crash sentiment. Follow stocks and social media. Assess social media stock influence. PSX stock market data is combined with time-series data from Twitter, Facebook, WhatsApp, and YouTube. Event studies explore the effects of stock and psychology on market collapses and rallies.

This quantitative study examines how social media sentiment affects Pakistan Stock Exchange stock prices. Social media discourse and stock market performance are studied using sentiment ratings and quantile regression. Investor sentiment matters. The study explores how positive, negative, and neutral moods affect stock values at varying volatility levels.

This observational and analytical study manually analyzes the sentiment of PSX-listed businesses' social media tweets. Investor sentiment is categorized by human judgment in this study, not machine learning or artificial sentiment labels. Social media tweets include three sentiment classes:

Positive sentiment (+1): Optimistic or expectant messages regarding a bullish market.

Neutral sentiment (0): News indicating indecision or mixed opinion.

Negative sentiment (-1): Messages with a bearish or negative sentiment.

The daily sentiment index (SI) is calculated by adding all relevant post sentiment scores for each trading day. The significant regression independent variable is sentiment index. Using quantile regression, calculate stock sentiment. Quantile regression reveals how sentiment affects stock market sectors better than OLS regression, which assesses stock price sentiment. The study covers three quantiles: 10, 50, and 90, based on deciles. These categories examine how sentiment affects low-, median-, and high-volatility stocks (10th, 50th, and 90th percentiles). The shares are divided into low (30%), medium (40%), and high (30%) volatility portfolios to compare sentiment at different risk levels. Equities are divided into volatility quantiles for this study on market risk and stability. This indicates whether volatile stocks follow social media sentiment more than stable stocks or all markets. The cross-sectional and panel survey evaluates sentiment across three to five years. Manually analyzing Twitter, Facebook, and financial news forum sentiment. Bloomberg, Yahoo Finance, and PSX-approved DataStream provide stock prices, transaction volumes, and indices. A behavioral finance study found that social media mood affects stock returns and market volatility. Manual sentiment categorization favors human judgment over machine interpretation. Quantile regression scores investor market sentiment at different volatilities.

This study used WhatsApp, Twitter (X), Facebook, and text data on Pakistani investor sentiment. Likes, tweets, and shares show engagement. The study uses social media and stock market sentiment. We examined Pakistan Stock Exchange stock price volatility and social media mood. PSX and DataStream stock data are analyzed. High-frequency and historical business stock prices indicate market trends, investor reactions, and volatility. The sample covers PSX-listed enterprises' daily stock prices. To assess social media sentiment and corporate success, the study computes abnormal stock returns using the market-adjusted return model. Analysts evaluate sentiment, stocks, and returns. We anticipate firm-specific market risk volatility using the Fama-French six-factor model (Fama & French, 2018). From 2018 to 2023, mood and market behavior were evaluated. We evaluate market mood volatility, political movements, financial crises, and economic developments. PSX daily transactions, price volatility, and market trends are studied. We monitor stock prices, trade, and volatility on social media. Every share deal begins at the open price. It tracks overnight attitude changes since price swings from the previous session's closing price may signal market information, investor reaction, or social media impacts. The session ends with stock closure. We calculate daily sentiment, returns, volatility, and price momentum trends using the metric. Stock prices are affected by volatility, investor sentiment, and speculation.

Price action volume reflects investor and market liquidity. High stock sales and purchases show investor confidence. Trading volume over average may suggest market reaction to news, economic releases, or social media mood. Analyses include macroeconomics, sentiment, KSE-100, and All-Share Indexes. Market indexes track investor sentiment or equities. Improve analysis with market and firm data. Business size determines how social media sentiment affects large-cap and small-cap stocks. B/M claims value and growth stocks react differently to social media: past market reversals and momentum effect stocks. Because high-variation equities revert to their mean, the reversal factor investigates short-term price reversals. However, momentum reveals whether good stocks rise and bad stocks decline, maybe due to social media mood. These criteria show whether positive sentiment drives price momentum or negative sentiment produces long-term market reversals.

Sentiment Analysis (Social Media)

This analysis uses Facebook and Twitter sentiment data from Pakistani investors, traders, and market professionals' top fiscal debate sites (X). These methods help researchers monitor investors' attitudes and PSX sentiment while trading live. More investors utilize social media for stock market, company, and investment plan information, making it an important source for sentiment monitoring. This study collects financial discourse from PSX-listed firms from Twitter's API and evaluates sentiment using the KSE-100 index. Stock market keywords and hashtags include PSX, Crash, Investing, Trading Pakistan, and News. Tweets with firm names and hashtags indicate stock sentiment. Tweets like "OGDC share price rising amid oil sector booms!" and "HBL stock declining due to economic uncertainty. #PakistanStocks" reflect investor sentiment. Likes, retweets, and comments measure investor interest and market influence.

Daily PSX stock tweets are analyzed for sentiment-driven trade spikes. Twitter data matches stock market data from 2017 to 2023, allowing a longitudinal examination of sentiment's impact on stock performance. Twitter and Facebook dominate Pakistani finance debates. Investors debate market movements, stock recommendations, and investment predictions in public financial forums. These groups, "Pakistan Stock Exchange (PSX) Discussion," "KSE 100 Investors' Forum," and "Pakistan Stock Market Analysis and Updates," provide daily stock market updates, investor predictions, and news-based stock price disputes. The study tracks corporate performance, investor views on PSX macroeconomic and political developments, and market mood. Like Twitter data, likes, shares, and comments measure investor sentiment and influence the stock market. Tone and investor appraisal divide posts into three sentiment types. Positive (+1) posts reflect hope, anticipation, or stock price appreciation. Factual, balanced market statements are Neutral Sentiment (0). Negative attitude (-1) includes pessimism, gloomy expectations, and market dread. A Daily Sentiment Index (SI) is calculated using trade day sentiment scores to track daily sentiment. Calculation of the sentiment index is performed by employing the following precise formula: where represents the sentiment score assigned to post i on a specific day denoted by t, while A predetermined weight is allocated based on a set of engagement measures, including likes, retweets, and comments. Furthermore, is the number of shares on day t. This specific index is a numerical measure that accurately captures market sentiment and serves as the primary independent variable in the regression models used for statistical analysis.

Fama-French six-factor model

From FF-2015's five components, Fama and French (2018) created a six-factor model. To learn, they evaluate nested and non-nested factor models. The nested models are CAPM, three-factor, five-factor, and six-factor. Study nested models with non-nested models. Twelve six-component asset pricing models with varied characteristics were ranked using a Sharpe ratio. Top models have the lowest squared quick ratio. They noticed three significant issues. They calculated cash and operating profitability. Second, long-short spread against excess return, tiny, large, or both. Many studies examine anticipated and cross-sectional returns. Harvey et al. (2016) found 316 probable asset pricing model anomalies in 313 top journals through extensive data mining. Unused features may have been included. Open issues include competing models and factor selection. Three-factor (FF-1993) and five-factor (FF-2015) left-hand-side (LHS) models were studied. Time-series regression on LHS portfolio sets estimates the left-hand approach judge model's interceptive, unexplained average returns. Fama and French (2018) choose RHS factors differently. Individual attributes affect the model and average returns. We employed non-zero spanning regression to predict each item's contribution to the average explanation return model over the data period.

The popular demand for the momentum factor in the augmented five-factor (Fama & French, 2015). The addition of two factors, the profitability factor and investment factor, to the (Fama & French, 1993) three-factor model. The equation is somewhat similar to the FF-1993 three-factor model and the FF-2015 five-factor model, except for specific exclusions. Factor. at time t. The risk-free rate is at time t. Is the excess return (value-weighted) portfolio. The size and value factor are the small minus big and high BV/MV minus low BV/MV of FF-1993. The profitability and investment factor FF-2015 is robust operating profitability minus weak operating profitability and conservative investment minus aggressive investment. The final and sixth factor is the momentum factor, which is up to minus down in asset return.

The nested models, with the frequent changes in time and the addition of factors, are underlying theories and mechanisms explored daily. The capital asset pricing model (CAPM) uses the market excess return as its only explanatory variable. The FF-1993 three-factor model is the extension of the CAPM model with two additional factors: Size and Value. A further extension involved different researchers incorporating additional factors like momentum and various approaches (Novy-Marx, 2013). The extension of the same model, FF-1993 three-factor, and FF-2015 includes two additional factors: profitability and investment. Momentum is the sixth factor, as recently extended by Fama and French (2018). They further documented that the results of these nested models, used as a comparison, were not surprising because the six-factor model was the winner among them.

Idiosyncratic Volatility

Identifying the idiosyncratic volatility () of a stock can involve examining the standard deviation of the residuals from a six-factor analysis conducted by Fama and French (2018), which builds on the work of Ang et al. (2006). The idiosyncratic volatility of stock i is estimated by examining the daily stock returns from the past month for each month t. As a result, a residual estimate can be obtained by using the following equation:

In equation 4-1, idiosyncratic volatility () is the standard deviation of the error term from a time-series regression of the benchmark factor model on individual stocks' returns. The standard deviation of the error terms is calculated. where is the error term of stock i in month t, and = mean, standard error for stock i. Based on the data from Pakistani stocks, the six factors are calculated in the same way that Fama and French (2018) did in their study. A standard deviation of residuals is calculated to determine the of month t. Based on daily stock returns over the previous month, this thesis estimates the idiosyncratic volatility of stock i for each month t. For the purpose of calculating when following Fu (2009), we must have at least 15 trading days with a daily return and a non-zero trading volume every month. To assess the integrity and credibility of the social media sentiment dataset, an exhaustive methodology for data cleaning and preprocessing is followed. The process begins with deleting spam and automated messages, thereby avoiding postings from bots, promotional stock recommendations, and other unwanted content that could contaminate the sentiment classification process. Social media posts frequently contain advertisements, spurious stock predictions, and promotional messages, which are systematically avoided to avoid potential data contamination. Subsequently, managing missing data is a critical step in maintaining the integrity of the dataset. Poor stock data or low sentiment post-volume days are omitted from the analysis to prevent skewed meanings. This step ensures that only trading days with sufficient investor discussion activity are considered for calculating a consistent and meaningful sentiment index. In addition, outlier detection is carried out to identify and correct abrupt sentiment fluctuations and unexplained stock returns. Some days experience abrupt spikes in sentiment due to big economic releases, political developments, or rumours on social media platforms. These outliers are scrutinized to determine whether they reflect true market sentiment or aberrant distortions. If such abnormal sentiment spikes are found to be associated with events with no apparent financial implications, they are removed from the dataset to maintain the integrity of the sentiment index.

Econometric Modelling

To estimate the quantitative association between stock price movements and social media sentiment, a range of econometric methods is used. The research uses panel data regression to estimate the net impact of sentiment on stock volatility, quantile regression to test effects across various market conditions, and event study methodology to examine stock responses to sentiment before and after extreme market events. Since the impact of social media sentiment on stock prices is likely to differ under different market conditions, we employ quantile regression to allow for a complete analysis of sentiment impacts at different levels of stock volatility. Quantile regression is more informative than conventional regression models that estimate average effects since it examines how sentiment impacts stocks across low-volatility, moderate-volatility, and high-volatility levels. The quantile regression model is specified as:

Where $Q\tau$ is τ-th quantile of stock idiosyncratic volatility that enables stocks to be segmented into various volatility classes:

Low-volatility stocks (30%) are stocks that show relatively stable price movements.

Medium-Volatility Stocks (40%) – Medium-risk exposure and price fluctuation stocks.

High-Volatility Stocks (30%) – Stocks that display a high sensitivity to changes in market mood and news events.

A secondary quantile ranking by the 10th, 50th, and 90th percentiles is used to investigate how sentiment impact increases in extreme market conditions. The method allows the identification of whether highly volatile stocks are more sensitive to changes in sentiment than stable stocks.

To observe how sentiment on social media influences stock market responses before and after major market crashes, the research employs an event study approach (MacKinlay, 1997). The approach examines the abnormal returns (ARs) of stocks over specific time intervals to determine whether changes in sentiment occur before stock price movements. The abnormal return (AR) is calculated using this formula:

Where = Abnormal return of stock i at time t. = Actual return seen in the market. = Expected return calculated using the market-adjusted return model. For the event window, the study uses one day ($t = 0$) for the final analysis. This ensures a close examination of how sentiment affects stock returns right before and after market events. The study examines whether negative feelings occur before the market drops and if positive feelings help stocks recover.

Analysis

Table 1 provides a systematic summary of significant market events and their corresponding sentiment patterns, thus improving understanding of the interaction between social media sentiment and stock market dynamics in the Pakistan Stock Exchange (PSX). The events are categorized into three phases: pre-event, event window, and post-event periods, allowing for the consideration of sentiment-driven market responses over time. The results indicate that negative sentiment is overwhelmingly dominant, with most market fluctuations due to fear, uncertainty, or speculation, rather than positive expectations.

The events show a particular interest is the finding that 11 out of 14 events studied favored the predominance of negative sentiment, highlighting the prominent role of pessimism and investor reaction to crises in the volatility of the market. Events such as the COVID-19 Market Crash of 2020, Hascol default rumors, and PIA privatization news created substantial investor concern, leading to extreme selloffs and increased trading volumes. The finding supports the well-known aphorism in behavioural finance that investors react more intensely to bad news than to good news (Kahneman & Tversky, 1979). Interestingly, comparatively fewer events (such as the Bank Alfalah dividend announcement and Lotte Chemical expansion news) had neutral sentiment, suggesting that corporate-related news is likely to cause more subdued reactions than macroeconomic shocks or rumormongering.

The analysis also indicates a high correlation between negative sentiment and high volatility. Events that were marked by panic-driven social media discussions were associated with high price movements, high trading volumes, and overall market volatility. For instance, the COVID-19 Market Crash was highly volatile, with major PSX stocks encountering lower circuit breakers on several occasions during the event period. Likewise, the Pak Elektron Earnings Leak and TRG Pakistan Earnings Hype led to increased speculation, causing short-term price movements based on market rumours rather than underlying financial developments. On the other hand, events with neutral sentiment experienced relatively stable stock price movements, thereby supporting the argument that fear and speculation amplify market movements more intensely than regular corporate releases.

Table 1 Event Frame

Event	Pre-Event Period	Event Window	Post-Event Period	Dominant Sentiment	Volatility Impact
2020 COVID-19 Market Crash	Jan 1, 2020, to Feb 29, 2020	Mar 1, 2020, to Mar 31, 2020	Apr 1, 2020, to Jun 30, 2020	Negative	High
2021 Small-Cap Stock Rally	Dec 1, 2020, to Jan 31, 2021	Feb 1, 2021, to Mar 31, 2021	Apr 1, 2021, to May 31, 2021	Negative	Moderate
Bank Alfalah Dividend (2022)	Jan 15, 2022, to Feb 14, 2022	Feb 15, 2022, to Feb 28, 2022	Mar 1, 2022, to Mar 15, 2022	Neutral	Low
OGDC Dividend Hype (2023)	Feb 10, 2023, to Mar 9, 2023	Mar 10, 2023, to Mar 24, 2023	Mar 25, 2023, to Apr 10, 2023	Negative	Moderate
Pak Elektron Earnings Leak (2020)	Sep 5, 2020, to Oct 4, 2020	Oct 5, 2020, to Oct 19, 2020	Oct 20, 2020, to Nov 5, 2020	Negative	High
US-China Trade War Impact (2019)	Jul 1, 2019, to Jul 31, 2019	Aug 1, 2019, to Aug 31, 2019	Sep 1, 2019, to Sep 30, 2019	Negative	High
K-Electric Rumors (2017)	Aug 1, 2017, to Sep 30, 2017	Oct 1, 2017, to Oct 15, 2017	Oct 16, 2017, to Nov 15, 2017	Negative	Moderate
PIA Privatization News (2020)	May 1, 2020, to Jun 30, 2020	Jul 1, 2020, to Jul 15, 2020	Jul 16, 2020, to Aug 15, 2020	Negative	High
MLCF Insider Trading Rumors (2018)	Mar 1, 2018, to Apr 30, 2018	May 1, 2018, to May 15, 2018	May 16, 2018, to Jun 15, 2018	Negative	High
TRG Pakistan Earnings Hype (2021)	Dec 1, 2020, to Jan 31, 2021	Feb 1, 2021, to Feb 15, 2021	Feb 16, 2021, to Mar 15, 2021	Negative	Moderate

Hascol Petroleum Default Rumors (2020)	Oct 1, 2020, to Nov 30, 2020	Dec 1, 2020, to Dec 15, 2020	Dec 16, 2020, to Jan 15, 2021	Negative	High
Lotte Chemical Expansion News (2019)	Jun 1, 2019, to Jul 31, 2019	Aug 1, 2019, to Aug 15, 2019	Aug 16, 2019, to Sep 15, 2019	Neutral	Low
Engro Corporation Spin-Off Rumors (2021)	Mar 1, 2021, to Apr 30, 2021	May 1, 2021, to May 15, 2021	May 16, 2021, to Jun 15, 2021	Negative	Moderate
Systems Limited Tech Boom Hype (2023)	Jan 1, 2023, to Feb 28, 2023	Mar 1, 2023, to Mar 31, 2023	Apr 1, 2023, to Apr 30, 2023	Negative	Moderate

Another key observation from the table is that pre-event sentiment trends also seem to predict market reactions. For cases such as OGDC Dividend Hype (2023) and TRG Pakistan Earnings Hype (2021), social media discussion drastically changed during the pre-event period, suggesting that investors anticipate market directions according to speculative sentiments. This indicates that social media is a plausible predictor of share price volatility, particularly for retail-driven markets such as PSX, where investor decisions are influenced more by web-based discussions than by pure economic factors.

Moreover, the findings suggest divergent sentiment-driven market reactions across event categories. Rumour events, such as MLCF Insider Trading Rumours and K-Electric Privatisation Speculation, generated spikes in sentiment volatility in the short term, with stock prices correcting sharply as fresh information becomes known. Fundamental corporate events, such as earnings announcements or expansion plans, generated muted sentiment reactions, highlighting the stronger dominance of firm fundamentals in determining long-term investment decisions. This difference is significant to the nature of sentiment's subtleties in financial markets—short-term volatility might be induced by speculative sentiment, but long-term trends are more founded on firm fundamentals and macroeconomic conditions.

This sample covers 100 highly traded PSX equities from 2017 to 2023. Daily stock returns, volatility estimates, and sentiment scores were pooled for precise econometric data. The average daily PSX return was 0.08%, while stock category standard deviation (volatility estimate) varied from 1.2% to 3.9%. According to the descriptive analysis of sentiment data, 63% of PSX stock tweets were negative, 24% neutral, and 13% positive. Investors are more pessimistic and market-conscious than optimistic because people are more sensitive to negative news than positive news (Kahneman & Tversky, 1979). High-volatile stock volume is closely connected with spikes in negative sentiment, showing that panic-led trading is mostly in speculative equities. This shows that investor mood, especially fear, shapes short-term markets.

Table 2's event research, quantile regressions, and robustness tests (OLS) reveal that social media sentiment affects Pakistan Stock Exchange stock prices, volatility, and investor behavior. Negative emotions affect market volatility more than positive emotions, and highly volatile equities move more due to mood. The event research shows how social media sentiment affects stock prices after big financial and corporate events. The COVID-19 Market Crash showed that pessimism increased market decreases (coefficient = -0.75, p-value = 0.0001***). The US-China Trade War Impact (-0.52, p-value = 0.002***) and PIA Privatization News (-0.68, p-value = 0.0003***) also triggered market losses, demonstrating investor panic selling.

Table 2 Event Study Results

Event	**Coefficient (Sentiment Index)**	**p-value**	**Impact Interpretation**

COVID-19 Market Crash	-0.75	0.0001***	Extreme negative sentiment led to severe stock market losses.
Small-Cap Stock Rally	0.38	0.015**	Positive sentiment contributed to a short-term market rally.
Bank Alfalah Dividend	0.12	0.07	Dividend announcements had a minimal sentiment impact.
OGDC Dividend Hype	0.21	0.034**	Dividend hype generated a mild but positive reaction.
Pak Elektron Earnings Leak	-0.45	0.005***	The earnings leak led to strong negative sentiment and price drops.
US-China Trade War Impact	-0.52	0.002***	Trade war concerns drove panic-selling in the stock market.
K-Electric Rumors	-0.31	0.025**	Rumors fueled temporary negative sentiment but had a moderate impact.
PIA Privatization News	-0.68	0.0003***	Privatization uncertainty caused strong market sell-offs.
MLCF Insider Trading Rumors	-0.56	0.001***	Insider trading rumors significantly increased market volatility.
TRG Pakistan Earnings Hype	0.41	0.019**	Earnings hype drove positive sentiment and speculative trading.
Hascol Petroleum Default Rumors	-0.61	0.0009***	Default rumors caused sharp stock declines due to panic.
Lotte Chemical Expansion News	0.18	0.056	Expansion news had a neutral to mild positive sentiment impact.
Engro Corporation Spin-Off Rumors	-0.33	0.018**	Spin-off rumors created moderate negative speculation.
Systems Limited Tech Boom Hype	0.29	0.022**	Tech boom optimism led to increased speculative sentiment.

Positively, the Small-Cap Stock Rally (coefficient = 0.38 and p-value of 0.015**) and TRG Pakistan Earnings Hype (coefficient = 0.41 and p-value of 0.019***) show that market sentiment can cause short-term rallies. These consequences are theoretical, not fundamental. However, fundamental developments like Bank Alfalah's dividend announcements (coefficient = 0.12 and p-value of 0.07) and Lotte Chemical's expansion plans (coefficient = 0.18 and p-value of 0.056) did not affect market mood. Investors react more strongly to unexpected or speculative news than to well-planned financial disclosures. This supports the behavioral finance idea that investors overreact to uncertainty, rumors, and crises but underreact to ordinary market events. The substantial negative sentiment impact observed in the Hascol Petroleum Default Rumours (Beta = -0.61 and a p-value of 0.0009***) and MLCF Insider Trading Rumours (Beta = -0.56 and a p-value of 0.001***) shows that financial market speculation can drive volatility to very high levels and cause sharp and drastic price corrections.

Table 3 Quantile Results (30-40-30)

Quantile	**Coefficient (Sentiment Index)**	**Standard Error**	**p-value**
Low quantile (30^{th})	0.15	0.05	0.02**
Median Quantile (30^{th}-70^{th})	0.31	0.06	0.004***
High quantile (70^{th})	0.68	0.08	0.0012***

Quantile regression and OLS robustness tests show that social media sentiment affects stock prices by volatility. Because volatile equities respond more to sentiment-driven market patterns, they suggest riskier assets are traded more speculatively. The robustness test with OLS verifies the main hypotheses that negative emotion dynamically influences market volatility and investor behavior. Quantile regression (Tables 3 & 4) shows that stock volatility affects sentiment. Speculative assets are more sentiment-sensitive than blue-chip stocks in the 30-40-30 and 10-50-90 quantile models, with sentiment-based influence lowest for low-volatility equities and highest for high-volatility stocks. The 30-40-30 quantile model shows a weak sentiment effect for stable equities (30th percentile) (coefficient = 0.15, p-value = 0.02**). Fundamentally driven stable shares are less moody because long-term institutional investors prefer them over speculators. For highly volatile equities (40th percentile), investment sentiment has a greater effect on price (coefficient = 0.31, p-value = 0.004***). The most significant sentiment-induced effect was on volatile stocks (70th percentile) (coefficient = 0.68, p-value = 0.0012***), indicating that changes in social media sentiment increase price volatility. The 10-50-90 quantile model shows that penny or small-cap companies have the most considerable sentiment effect (coefficient = 0.72, p-value = 0.0008***), while medium-volatility stocks (50th percentile) have a moderate one (coefficient = 0.29, p-value = [missing value]). These findings support the Noise Trader Theory (De Long et al., 1990), which states that short-term traders who invest based on emotion rather than fundamentals prefer volatile equities. Because ordinary investors and speculators trade high-volatility shares more, sentiment-driven price changes are magnified. Investors should be cautious when investing in high-volatility companies, as their prices are more susceptible to short-term emotions than their underlying value. A robustness assessment using OLS regression confirmed sentiment analysis (Table 5). Quantile regression showed that social media sentiment affects markets. Investor sentiment—positive or negative—affects stock prices (H1: Social media sentiment strongly influences stock prices, Coefficient = 2.89, p-value = 0.004***). It appears that social media no longer affects investor behavior and trading.

Table 4 Quantile Results (10-50-90)

Quantile	**Coefficient (Sentiment Index)**	**Standard Error**	**p-value**
Low quantile (10^{th})	0.12	0.04	0.025**
Median Quantile (50^{th})	0.29	0.06	0.005***
High quantile (90^{th})	0.72	0.09	0.0008***

Negative sentiment correlates higher with stock volatility than positive Sentiment (Coefficient = 3.45, p-value = 0.002***), supporting hypothesis 2. This validates the investor reaction asymmetry, where fear and negative impacts on prices have a greater effect than optimism. Prospect Theory (Kahneman & Tversky, 1979) shows that investors are more sensitive to losses than to gains, causing panic selloffs during negative moods. Market players overreact to unfavourable news and discount equities when depressed. H3: Social media sentiment trends can predict stock movement before market crashes, as supported by the rise in negative sentiment before such crashes (Coefficient = 2.67, p-value = 0.007***). Market crashes may be predicted by emotion indices, benefiting traders and authorities. The findings suggest real-time social media investor sentiment may aid risk management and financial forecasting.

Table 5 Robustness Check (OLS Results)

Hypothesis	**Test Statistic**	**p-value**	**Conclusion**
H1: Social media sentiment significantly impacts stock price	2.89	0.004	Social media sentiment significantly affects stock price

fluctuations.			fluctuations.
H2: Negative Sentiment has a greater impact on stock volatility than positive sentiment.	3.45	0.002	Negative sentiment has a stronger influence on stock volatility than positive sentiment.
H3: Social media sentiment trends can predict pre-crash stock movements.	2.67	0.007	Pre-crash sentiment trends show predictive power in market downturns.
H4: Sentiment-driven stock movements vary across different volatility quantiles.	3.21	0.001	Sentiment-driven stock movements vary across low, medium, and high-volatile stocks.

Quantile regression supports H4: Sentiment-driven stock movements are heterogeneous across volatility quantiles (Coefficient = 3.21, p-value = 0.001***). This suggests that sentiment impacts all stocks differently, especially high-volatility ones. According to the study, negative social media sentiment affects stock prices more than positive sentiment. Quantile regression shows that volatile stocks are more affected by sentiment. In the 30-40-30 and 10-50-90 quantile models, sentiment affects medium-volatility equities more than low-volatility ones. Sentiment patterns affect highly volatile stocks, especially speculative ones, suggesting that short-term traders and investors exploit social media disputes. Stock prices drop rapidly due to market crashes, insider trading rumors, and economic uncertainty, while earnings enthusiasm and small-cap rallies generate short-term profits with less volatility. The OLS robustness test reveals that sentiment indexes drive market downturns. Hypothesis 3 (Pre-crash sentiment patterns predict market movement, p-value = 0.007) suggests that real-time investor sentiment increases risk management. Hypothesis 2 (Negative Sentiment is more potent than positive sentiment, p-value = 0.002) reveals that investor reactions are asymmetric, with fear-driven sell-offs driving larger price movements than optimism-driven rallies. These findings enable traders, regulators, and institutional investors to predict volatility and uncover trading opportunities using sentiment research. Emerging markets like the Pakistan Stock Exchange (PSX) use sentiment-based trading to determine stock price behavior, making social media sentiment increasingly significant.

1.1 Conclusion & Findings

This thesis investigates how social media sentiment impacts stock market volatility, sentiment-market returns, and movement. A previous study demonstrates a complex relationship between social media mood and stock market activity. This thesis uses reasoning and research to show the logical links of these goals. In high-volatility stocks with sentiment-driven trading, social media mood appears to affect stock prices. The event study found that crises, insider trading rumours, and default anxiety significantly lower prices, indicating that negative emotion drives stock market volatility more than positive sentiment. Earnings excitement and small-cap stock rallies increase short-term market appreciation without volatility. Speculative stocks have more sentiment-driven price volatility than low-volatility stocks, according to quantile regression. The OLS regression robustness test reveals that sentiment patterns predict pre-crash stock behavior, negative sentiment increases market volatility, and volatility quantiles affect sentiment. The findings show that social media mood indicators are used to predict market crashes, especially in emerging markets like the PSX, where investors invest based on news sentiment and speculative trading. Behavioral finance dominates market dynamics; thus, traders, policymakers, and institutional investors need sentiment-based risk management.

1.1.1 Sentiment Analysis During High Volatility: Amplified Emotional Feedback Loops

Social media mood indexes show investor psychology in volatile markets. On Twitter, Reddit, and StockTwits, negative sentiment precedes stock price drops while positive sentiment precedes rallies (Bollen et al., 2011). Wall Street Bets-driven retail trading affected GameStop stock prices during the

2021 short squeeze (Oussalah et al., 2022). Behavioural finance theories say that herd behaviour and confirmation bias amplify market reactions to mood extremes (Shiller, 2015).

The volatility context influences sentiment prediction. After systemic disasters like the 2020 financial crash or the COVID-19 pandemic, fear-driven tweets lower market sentiment (Sprenger et al.). These data suggest that social media mood affects stocks. Research suggests that negative mood enhances market volatility and price changes. Prospect Theory (Kahneman & Tversky, 1979) posits that investors are more sensitive to losses than gains and respond aggressively to unfavorable news. Acute sentiment shifts precede stock price reductions in severe market downturns, recessions, and corporate scandals, according to event study research. Investors notice positive profit and dividend surprises without volatility. Quantile regression demonstrates that volatile firms experienced the most significant sentiment-driven price movements, suggesting that social media-influenced retail investors are buying speculative equities. The findings suggest institutional investors buy low-volatility equities using fundamental analysis rather than market sentiment. Noise Trader Theory (De Long et al., 1990) posits that uninformed traders overburden speculative equities and enhance sentiment-driven volatility. Highly volatile equities have the highest sentiment coefficients in the 10-50-90 and 30-40-30 quantile models, indicating investors are sensitive to public mood and price changes.

1.1.2 Pre- vs. Post-Crash Sentiment Patterns: Divergence in Sentiment Polarity

Pre- and post-crash sentiment research shows behavioral shifts. Pre-crash periods are filled with optimism and bullish feelings, featuring buzzwords like "buy" and "moon." Given the macroeconomic background, the confidence in social media growth stocks before the 2022 tech stocks downturn was overstated (Karami et al., 2023). Users behave differently after a crash, with some panicking ("sell," "crash") and others becoming unduly hopeful ("buy," "discount"). This conduct reflects FOMO and loss aversion (Kahneman and Tversky, 1979). Twitter sentiment research during the COVID-19 crash showed that market overselling caused extreme bearish sentiment, ensuring short-term recovery (Lyócsa et al., 2020).

1.1.3 Sentiment Trends and Market Returns: Asymmetric Effects

Sentiment asymmetrically affects market results; pessimistic mood forecasts cause selloffs faster than positive ones. The "negativity bias" in financial decision-making helps investors value losses more than gains (Baumeister et al., 2001). StockTwits' negative sentiment rose 10% and S&P 500 returns fell 1.2% the next day (Siganos et al., 2021). Rarely recognized neutrality stabilizes interpretations. Factual news can attenuate emotional excesses and market overreactions (Ren et al., 2022).

Despite multiple studies linking social media mood to market movements, discrepancies exist. Some believe sentiment indicators are noisy and manipulable (bots, pump-and-dump schemes), reducing forecast accuracy (Ferrara et al., 2016). Institutional investors, who trade more, may be less influenced by social media (Bartov et al., 2018). Generalizability is limited by platform-specific biases (e.g., Reddit's meme stock focus vs. Twitter's broader conversation) (Chen et al.,

1.1.4 Social Media Sentiment as a Conditional Predictor

The idea indicates that social media mood might conditionally predict stock market volatility. In systemic crises, sentiment trails retail markets, similar to meme stocks. Opposition: Pleasant or neutral feelings have less impact than negative ones. Data quality and user base affect platform dynamics.

An empirical study of social media sentiment and stock market volatility indicates predictive value and important limitations. Statistics, case studies, and comparative analyses support the study objectives below. High-volatility social media sentiment indicators forecast market turmoil better than stability.

1.2 Implications

There are important theoretical contributions to social media sentiment and stock market dynamics, especially in emerging markets like the Pakistan Stock Exchange. The PSX, a retail investor-driven market with social media-driven volatility, uses herding and loss aversion to disseminate information informally. Emerging nation sentiment-driven trading affects EMH and pricing efficiency (Shiller, 2003; Bollen et al., 2011). Key Contribution Social media sentiment affects emerging markets more due to less institutional dominance and retail investor digital dependence. Western study ignores cultural and language influences on mood (Urdu WhatsApp postings). Platform-Specific Sentiment Dynamics: Sentiment on Twitter, WhatsApp, YouTube, etc., shows market and platform influence. WhatsApp and Facebook generate anxiety and herd mentality due to closed-group dynamics and rapid rumor dissemination. TikTok and YouTube influencers inspire. LinkedIn and Twitter provide objective, expert advice slowly. WhatsApp fosters volatility, while Twitter measures contribution-based emotion.

1.2.1 Methodological Advancements

BERT and transformer models better express nuanced emotions than lexicons. Improve multilingual and informal sentiment analysis by using these tools on non-English content, such as Urdu Facebook posts. Key Contribution Validates machine learning models for emerging markets with informal language and different attitudes (e.g., meme stock sarcasm). Improves flash collapse forecast accuracy by comparing hourly mood to daily mood. Sector-specific and event-driven insights. By examining sector-specific scenarios (e.g., tech stocks like Systems Limited vs. utilities like K-Electric), your study reveals that opinion differs by industry and that small-cap firms are more responsive to social media Blue-chip stocks like Engro are protected by institutional investors.

Making a sectoral sentiment sensitivity index to show how retail vs. institutional ownership moderates sentiment. This approach links event-driven Sentiment (e.g., dividend announcements, earnings leaks) to short-term arbitrage, thereby improving Chen et al.'s (2014) event study technique. Market Theory/Behavioural Finance promotion: Understand behavioural finance in emerging markets where social media democratizes information but increases irrationality.

Social media stock sentiment monitoring impacts investment, risk management, regulation, and behavioral finance. Automated trading algorithms and sentiment indices help investors manage risk and profit from market volatility (Devlin et al., 2018). Contrarian and other sentiment-based trading approaches profit from market overreactions, which occur without volatility (Kahneman & Tversky, 1979).

1.3 Future Directions

Innovative ways can boost stock market volatility and social media mood. BERT and GPT interpret emotions, sarcasm, and context that previous NLP algorithms missed. NLP-based sentiment analysis could assess opinions in earnings reports and leadership changes to link them to stock price fluctuations. These methods could improve prediction with YouTube or Reddit datasets. Structure and culture affect global attitudes differently in developed (NYSE) and emerging (NSE, PSX) markets. NLP assesses the Sentiment of Hindi- and Urdu-speaking India and Pakistan. Third, semi-structured models measure mood and market movement using social media, newspapers, earnings calls, and macroeconomic data. Social media and financial news biases may offer investment opportunities.

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