4 EXPOSE THE HIDDEN: INVESTOR SENTIMENT AND ANOMALY STRATEGIES IN EMERGING MARKET

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Abstract

Using anomaly techniques, this study examines the crucial role that sentiment in the market, news, and social media plays in forecasting stock returns. We used a simple regression model on a sample of public non-financial Pakistani stocks from 2009 to 2019. Our results show that, under anomalous strategies, the emerging companies are significantly impacted by sentiment in the market, news, and social media. Our results are in line with earlier research and refute a popular belief that has been contested in other studies, such as the notion that investor sentiment is less significant in emerging economies.

Keywords: Investor sentiment; Stock return; Anomaly strategy

JEL Classification: G10, G14, G4

1. Introduction

Stock pricing has been doing the rounds of finance literature for more than four decades now and asset pricing models not only evaluate the risk-return relationship but also play a key role in portfolio management process. Financial scientists have developed various stock pricing models comprising different aspects of risk factors. For example, the asset pricing models developed by Sharpe (1964) and Fama and French (1993) are the famous and extensively proficient model in the finance literature.

The capital asset pricing model (CAPM) was commonly used in the early 1970s. Later on, a couple of studies emphasize the other factors connecting to the risk and return relationship after the 1970s. For example, arbitrage pricing behaviour (Ross, 1976), intertemporal consumption deeds (Merton, 1973), the market value of the firm (Rosenberg et al., 1985), firm size

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(Reinganum, 1981; Keim, 1983), and firm' cash flow yield (Chan et al., 1991) are the factors having a significant impact on the stock return.

The model developed by (Sharpe, 1964; Lintner, 1965; Mossin, 1966) has been challenged by (Fama and French, 1992) with a considerable evidence that a single factor is not enough to predict the stock return efficiently introducing the value and size as an additional factor with market risk to predict the cross-sectional return. Further, investment and profitability with three factors have also been used by Fama and French (2015) which is again inefficient for the small stocks listed on the US stock market. However, the proportion of the small stock is negligible (Elliot et al., 2018). Conversely, Kubota and Takehara (2018) critically examine that profitability and investment factors have less power to predict the stock return. However, the contribution of value and size factors is unavoidable (Xie and Qu, 2016).

Efficient market hypothesis (EMH) assumes that asset prices fully reflect the market facts. Still, many studies challenge the validity of the EMH and introduce different trading strategies to show the biasness in the stock prices. The very famous trading strategies in the finance literature are anomaly strategies. Many studies (e.g., Banz, 1981; Basu, 2013; Novy-Marx, 2013; Stambaugh et al. 2012; Thomas and Zhang, 2002; Andries et al. 2017; Zaremba, 2015) document the anomaly strategies and prove that efficient market hypothesis does not exist in the real trading world. The sentiment-driven traders' remains in the market until the rational traders replace them from the market. Likewise, several studies (e.g., Bollen et al. 2011; Heston and Sinha, 2017; P H and Rishad, 2020; Petit et al. 2019; Stambaugh et al., 2012; Yang et al.2015; Kim and RYU, 2020; Lu et al. 2014; Mohsin et al. 2021) the role of investor sentiment in the market activities.

In this regard, we use the dataset of one of the emerging economies particularly Pakistan to test the implication of the anomaly strategies under the given news-, social media- and market-wide sentiment. Although, (Iqbal and Brooks, 2007; Mirza and Shahid, 2008) use the three-factor model and observe a significant contribution to the risk factor in the context of Pakistani stocks market. But a few of the previous studies examine the anomaly strategies under the sentiment-driven traders that might be an interesting topic in the context of Pakistan stock market. Most of the previous studies use the non-financial listed firms in the anomaly strategies but they have less focus on the emerging economies. However, the economic fundamentals of the emerging and advanced economies are not same as revealed by Fama and French (1998). We want to examine that how the trading behaviour of the emerging economies react toward the anomaly strategies. Pakistan stock exchange also has a different characteristic than the US stock market as examined by Khwaja and Mian (2005). We use a set of asset pricing anomalies, including asset turnover, sale, inventory turnover, asset growth, gross profit margin and debt issuance for the trading strategies. Based on each anomaly, we observe the long-position (short-position) in the uppermost-performing (lowest-performing) decile of the stock and the long minus short strategy in our empirical analysis.

Previous work proposes various proxies to construct the sentiment. As Petit et al., (2019) use indirect information and Baker and Wurgler (2006) use market-wide proxies to measure the investor sentiment. However, we use the market-, news and social media-based proxies to construct the investor sentiment accordingly. In this regard, we build the stockholder behavior exposed by the investor sentiment and its impact on return via anomaly trading strategies. This study uses a quarterly dataset of the non-financial firms listed on the Pakistan stock exchange[5] over 2009-2019. We collect the quarterly firm-specific anomaly' data, news (political and foreign investment news) data and social media trends from the Bloomberg database[6] and Google trends respectively. For the news data, we use a lexicon-based approach to convert the news into

[5] *www.psx.com.pk*

[6] *www.bloomberg.com*

meaningful numeral form to construct the news-based investor sentiment. Consequently, we use trading volume, market capitalization, high minus low market index, exchange reserves (ER), balance of trade and interest rate spread to construct the market wide investor sentiment. Subsequently, Google, Twitter, Express, OLX, Youtube, Facebook and porn webpage trends in Pakistan, are used to quantify the social media-based investor sentiment. Through a panel regression approach, we have found that investor sentiment has a significant impact in the anomaly based trading strategies.

This study offers several ground-breaking contributions. It: (1) evaluates the long-short anomaly strategies along with investor sentiment; (2) introduces three separate investor sentiment using (news-, market- and social media-based proxies); (3) determines which strategy is profitable in the context of the Pakistani stock market. Our empirical outcomes narrate that: (1) the anomaly strategies are applicable for the Pakistan stock exchange and the stock traders can earn an abnormal return in the stock market; (2) investor sentiment can also elucidate the variation in the stock price in the context of Pakistan stock market.

The rest of the paper proceeds as follows; Section 2 briefly overview the previous work and set out the hypothesis. Section 3 deliberates the methodology and data collection procedure. Section 4 offers empirical results and discussion. Finally, we provide the conclusion of the study in the last section.

2. Literature review

2.1 Anomaly strategies

The term 'anomaly' has grabbed not only the attention of traders and investors throughout the investment choice process, but it has also earned significant importance in the financial area today. The theme of anomaly theory is the emotional or irrational behaviour of traders, which is in stark contrast to conventional finance theory, which is based solely on rationality, as demonstrated by (Fama and French, 1992). The term 'anomaly' is commonly associated with multiple fields of science such as music, linguistics, geography, meteorology, and astronomy, and it refers to an inequality of fundamental conditions or a divergence from normal equilibrium (Frankfurter and McGoun, 2001). However, anomalies are significant in determining business activity. For example, anomaly is a key factor that not only captures business risk but also leads to the forecasting of the firm's systemic errors (Lupu *et al.*, 2022).

Anomaly strategy is a debatable issue in the finance literature because it produces a bigger problem than the market-factor pricing model (Sharpe, 1964; Lintner, 1965). We document a set of anomalies following the previous literature. For example, Gross-profit to asset has been used by Novy-Marx (2013) and it is observed that high-gross profit firms earn abnormal returns than the low-gross profit firms. Investors also observe the firm's asset expansion strategy and react accordingly. As Cooper et al. (2008) examine that high asset growth firms earn a lower return and vice versa. Investors believe that lower former investment forecasts higher future return and vice versa. Xing (2008) also examine similar facts and confirm the adverse relation of past investment with future stock return. Investors also observe the price per share or earning per share as anomaly and relate it to the subsequent future return. Blume and Husic (1973) observe significant relation of price per share with stock return. Further, the stock traders also belief that lower past return on asset generate lower future return. Fama and French (2006) investigate that high profitability leads to an increase in the stock return and vice versa. Similarly, cash ratio also play an important role as Palazzo (2012) confirms the positive relationship between cash holding and stock return. In addition, accounting information has a substantial impact on the earning. Soliman (2008) narrates the positive association between stock return and asset turnover. The stocks traders believe that price to earnings ratio also predict the stock return, which negates the efficient market hypothesis. As Basu (2013) describes that the stock with lower price to earnings ratio has a higher return and vice versa. Moreover, the stock traders believe that debt issuance has a significant impact on stock prices as Spiess and Affleck-Graves (1999) scrutinize the impact of borrowing on the stock performance and confirm the future stock performance always follow the high debt volume of the past history. Stock traders also notice the fundamental analysis to predict stock performance. For example, Abarbanell and Bushee (1998) use different accounting fundamentals to predict future stock return. The literature describes several forms of anomalies and their importance in the world of finance.

2.2 Investor sentiment and stock return

Why does investor sentiment matter? It is a critical and debatable issue in the business and stock trading worlds. A large body of past study has examined the relationship between investor sentiment and stock market performance on an individual and aggregate basis. A variety of proxies for investor sentiment have been developed to reflect the elusive relationship with the stock market. Such sentiment proxies include survey-based, market-based, and media-based proxies, demonstrating the relevance of investor sentiment.

Investor psychology or sentiment has piqued the interest of stock traders, business analysts, and academics since the 'animal spirit' concept was introduced by (Keynes, 1936). According to classical theory, rational behaviour determines the equilibrium price level that contains the asset's inherent value. In contrast, over-optimists emphasize the importance of individual sentiments and emotions, which leads to price disequilibrium, which differs from the classical perspective. In this sense, speculative shock cannot be avoided, which are caused by investor sentiment (Baker and Wurgler, 2006). It is obviously evident that there is over-optimism, and stock traders must recognize the relevance of investor attitude in the trading arena. Without considering investor mood, the risk/cost of capital increases, which can lead to inefficient asset allocation in the portfolio process.

The stock market is subject to irrational elements such as politics, economics, technology, and finance. For example, political news or events can enhance or decrease stock returns in the US military, banking, and energy sectors (Tomic, Todorovic and Jaksic, 2023). The stock market is subject to irrational elements such as politics, economics, technology, and finance. For example, political news or events might cause a rise or drop in stock returns in the US military, banking, and energy sectors. On the other hand, information technology is an essential factor in defining business and tourism operations. People are well-informed by many sources of information, which plays a vital part in shaping their business-related behaviors (Nguyen, Nguyen and Tran, 2023). (Rehman *et al.*, 2021) has examined the importance of the foreign investment news based sentiment to determine the stock market activities in the case of Pakistani stock market. Further, (Muhammad, 2021) has observed the importance of the investor sentiment at aggregate market-, and firm-level activities in the case of Pakistani stock market.

The previous literature narrates the relation between stock return and investor sentiment (e.g., Baker and Wurgler, 2006; Huang et al., 2015; Petit et al., 2019). The importance of investor sentiment is not unavoidable and its impact on the variable and fixed financial instruments. As Çepni et al. (2020) recently have investigated the relation of investor sentiment with fixed financial instruments, especially using the US bond market data. They examine a short term significant impact of investor sentiment on the fixed income bond. Consequently, Khan et al. (2019) observe the relationship between investor sentiment and non-fixed financial instruments using the US stock market data. They confirm a strong relation of investor sentiment with the stock return for the short and medium periods. Subsequently, Sibley et al. (2016) also examine the strong association between investor sentiment and stock performance. Consequently, Li and Ran (2020) observe that investor sentiment has not only a significant impact on the market return but also predict the cross-sectional return in the case of Chinese stock market.

Numerous proxies have been used to measure the investor sentiment in the finance literature. Zhang et al. (2018) use news as a sentiment proxy to extract the public mood and its impact on the market activities. As Nisar and Yeung (2018) use social media to measure the sentiment and its impact on the stock return. On the other hand, market-wide proxies are immensely used to measure the investor sentiment. Likewise, Huang et al. (2015) and Baker and Wurgler (2006) use market wide proxies to measure the investor sentiment and its impact on the stock prices.

2.3 Related hypothesis

The objective of this empirical work is to authenticate the presence of investor sentiment and its influence on the stock return under the anomaly based strategies. If investor sentiment precisely signifies the inclination to take the investment decision, then irrationality may lead to changes in the market environment. With the support of previous finance literature, we can deduce that market, social media, and news signals are imperative to stock markets. A hypothesis that we suggest to examine is as follows:

> *Hypothesis: Investor sentiment has a direct impact on the long-short strategies of anomaly based sorted return.*

Novy-Marx (2013) has observed the significance of the anomaly based trading strategies. Stambaugh et al. (2012) have examined the significance of the investor sentiment and its impact on the anomaly based long-short trading strategy.

3. Data and methodology

We use the investor sentiment and anomaly-based sorted return level data of Pakistani non-financial firms. The sample comprised of data from 2009 to 2019 of non-financial firms listed on the Pakistan stock exchange. The previous literature shed a light on this issue that the information pattern has great link with stock performance (Cai et al., 2018). In this regard, we have used the news-, market-, and social media-based proxies to construct the investor sentiment separately and its impact on the stock return. Because the news has direct impact on the public mood (Ikizlerli et al., 2019). We collect the news (foreign investment news, political news) from the Bloomberg database over 2009-2019 and implement the lexicon-based method for the textual measurement. The reason to choose the foreign investment news is that foreign investment transports the technology (Desmet et al., 2008), escalate economic output (Altomonte and Pennings, 2009), augment commercial growth (Gunby et al., 2017; Shah et al. 2019). Likewise, the reason to choose political news is that it has a strong association with stock market and business activities (Al-Maadid et al. 2020; Braga-Alves, 2018; Rehman et al. 2021).

We use the State Bank of Pakistan[7] and Pakistan stock exchange to get the macroeconomic data and market-based proxies. We use RIPO, NIPO, TURN, DP and EQI as market-based proxies to measure the investor sentiment. Likewise, we have used social media platforms, such as Google, Express, offline express Pakistan (OLX), Youtube, porn webpage and Facebook trends in Pakistan, for the social media-based investor sentiment.

Firm-specific data, including the closing stock prices and anomaly data are obtained from the Bloomberg database. The saving certificate rate has been used as a proxy for the risk-free rate obtained from the official webpage of the State Bank of Pakistan (SBP). Table 1 and Table 2 narrate the variable's definition and summary statistics used in the empirical work.

[7] *www.spb.org.pk*

Table 1

Variable Definition

Variable	*Definition*
TV	Monthly market trading volume
Pn	Monthly political news score
Interest rate spread	The interest rate spread calculated by taking the difference between the riskless rate and KIBOR
High-Low_index	High minus low market index calculated by taking the difference of high and low market index
Fin	Foreign investment news score
$TV_{(t-1)}$	Lag value of monthly trading volume
$Pn_{(t-1)}$	Lag value of political news score
$fin_{(t-1)}$	Lag value of foreign investment news score
High-Low_index$_{(t-1)}$	Lag value of the high minus low index
$r_{i,t}$	Monthly individual stock return
WC	Working capital of the firm
ASTG	Asset growth of the firm
GPM	Gross profit margin
SALE	Annual sale of the firm
ATR	Asset turnover
DEBT_I	Change in debt of the firm
ITR	Inventory turnover

Table 1 narrates the empirical analysis's variable definition from three sources; Bloomberg, SBP, and PSX

Table 2

Descriptive statistics

Sentiment & anomaly	*N*	*Mean*	*Sd*	*Min*	*Max*
Monthly sentiment related observations					
Mkt_Cap	120	2.045e+12	9.946e+11	0	8.612e+12
Pol_ns	120	0.0167	0.126	-0.285	0.692
BOT	120	-9810.175	6057.74	-31178	-1034
TV_GS	118	0.087	0.391	-0.70	2.25
Ex_rate	119	98.23	12.11	79.08	138.69
Gold	119	2705.844	435.31	1828.51	3778.71
SDR	119	825.33	313.6	152.67	1435.59
Fdi_News	120	0.0318	0.0293	-0.0652	0.101
Facebook	120	55.05	27.91	6	100
OLX	120	56.88	33.03	2	96
Expr_new	120	43.03	20.64	17	100
Por	120	52.23	16.02	21	93

Youtube	120	34.83	19.32	11	100
Google	120	35.80	15.15	12	100
Twitter	120	44.43	23.10	0	100
$Sent^B$	120	4.47e-09	1.000	-1.077	3.875
$Sent^N$	120	3.41e-09	1.000	-2.390	5.346
$Sent^M$	120	2.15e-09	1.000	-1.570	4.236
Short, Long, Long-Short					
Short-leg-ATR	1,869	0.006	0.084	-0.153	0.115
Short-leg-DBT_I	1,869	0.046	0.104	-0.114	0.264
Short-leg-WC	1,869	0.167	0.503	-0.123	1.568
Short-leg-ITR	1,869	-0.001	0.076	-0.120	0.082
Short-leg-SALE	1,869	-0.002	0.074	-0.130	0.122
Short-leg-GPM	821	-0.010	0.036	-0.052	0.030
Long-leg-ATR	1,869	1.025	2.863	-0.071	9.049
Long-leg-DBT_I	1,869	0.195	0.558	-0.087	1.755
Long-leg-WC	1,869	0.817	2.327	-0.102	7.338
Long-leg-ITR	1,869	0.001	0.049	-0.104	0.078
Long-leg-SALE	1,869	0.489	1.385	-0.095	4.370
Long-leg-GPM	821	0.005	0.048	-0.045	0.063
Long-Short-ATR	1,869	1.019	2.829	-0.022	8.948
Long-Short-DBT_I	1,869	0.149	0.479	-0.067	1.490
Long-Short-WC	1,869	0.650	1.827	-0.054	5.770
Long-Short-ITR	1,869	0.003	0.046	-0.075	0.097
Long-Short-SALE	1,869	0.491	1.395	-0.092	4.399
Long-Short-GPM	821	0.015	0.017	-0.003	0.043

Table 2 describes the monthly (Panel A) and quarterly (Panel B & C) summary statistics of the data for the financial and non-financial sectors over the period 2009-2018.

3.1. Investor sentiment proxies

3.1.1. Market-wide sentiment proxies

We use Baker and Wurgler's (2006) available set of proxies, which includes the first day return of an initial public offering (RIPO), the number of NIPOs, market turnover (TURN), dividend premium (DP), and share of equity issuance (EQI). We collected the market-wide sentiment proxies from the Pakistan stock exchange and State bank of Pakistan.

3.1.2. Social media-based sentiment proxies

As far as the social media proxies are concerned, we used the media trends (Twitter, Google, Express, OLX, Youtube, porn videos and Facebook) to see how widespread was the use of those social media in Pakistan over 2009-2018. Khan et al., (2019) use the same procedure to measure the media-based investor sentiment and its impact on the US stock prices.

3.1.3. News-based sentiment proxies

Several textual measurement techniques, such as (word count, algorithm, etc.) have been suggested in the previous literature (e.g., Funke and Matsuda, 2006; Mangee, 2017). After collecting the foreign investment and political news data from the Bloomberg database, we employ the sentiment lexicon-based procedure via python to measure the text as recommended in previous study (Hutto and Gilbert, 2014). We get the news score after the five-step process. In the first step, the news file is pre-processed grammatically and syntactically with the given set of linguistic features. In the second step, we divide each word of the news file into the token. In the third step, we remove the worthless words from the file, such as (a, the, while, an, etc.). In the fourth step, we eliminate the punctuations from the text file. In the next step, we employ the dictionary-based technique via python to measure the polarity (positive, negative, compound) of the news file. Finally, we get the political news score (pn_t) and foreign investment news score (fin_t) of the *t* file dividing the difference in polarity by the compound polarity of the entire content as revealed in the equations (1) and (2) below.

$$fin_t = \frac{pos\_pol_t - neg\_pol_t}{comd\_pol_t} \quad (1)$$

$$pn_t = \frac{pos\_pol_t - neg\_pol_t}{comd\_pol_t} \quad (2)$$

Where $comd\_pol_t$, neg_pol_t and pos_pol_t narrate the compound, negative and positive polarity of the news file at time *t*. We follow the idea revealed by Calomiris & Mamaysky (2019), who use the negative and positive word list of the entire article to measure news score. We employ a quarterly average news score to construct the investor sentiment for the empirical analysis which shows a long term impact of news sentiment. As Piñeiro-Chousa et al., (2016) and Heston and Sinha (2017) have indicated the long-term news impact in their empirical work.

4. Measurement of independent and dependent variables

4.1. Independent variable

We build investor sentiment using principal component analysis and a variety of news-, market-, and social media-based sentiment proxies. To develop the news-based emotion, we employ political news and foreign investment news. Likewise, we employ Baker and Wurgler's (2006) available set of proxies, which includes the first day return of an initial public offering (RIPO), the number of NIPOs, market turnover (TURN), dividend premium (DP), and share of equity issuance (EQI). We use the data reported in Table 3.

Investor sentiment was employed as an independent variable, and the findings were derived using the principal component technique, as shown in Tables 3 and 4.

We define social media-, news-, and market-based investor sentiment using the data in Table 4, as illustrated in equations (3), (4), and (5), respectively.

$$Sent_t^B = 0.56(NIPO)_t + 0.51(RIPO)_t + 0.52(TURN)_t - 0.33(DP)_t + 0.17(EQI)_t \quad (3)$$

$$Sent_t^N = -0.71(Pn)_t + 0.7(fin)_t \quad (4)$$

$$Sent_t^M = 0.55(FB)_t + 0.30(OLX)_t + 0.11(YT)_t + 0.54(GL)_t + 0.54(TW)_t - 0.05(EX)_t \quad (5)$$

Where $Sent_t^B$, $Sent_t^N$ and $Sent_t^M$ narrate the market-, news-, and social media-based investor sentiment respectively.

Table 3

Eigenvalue and Contribution Ratio of Investor Sentiment

	Market-Based Sentiment			Social Media-Based Sentiment			News-based Sentiment		
					N_Sent			MED_Sent	
Components	**Eigenvalues**	**Contribution Ratio**	**Cumulative**	**Eigenvalues**	**Contribution Ratio**	**Cumulative**	**Eigenvalues**	**Contribution Ratio**	**Cumulative**
1	2.54	0.50	0.50	2.94	0.49	0.49	1.09	0.54	0.54
2	1.32	0.26	0.77	2.24	0.37	0.86	0.91	0.45	1.00
3	0.57	0.11	0.88	0.38	0.06	0.93			
4	0.38	0.07	0.96	0.20	0.03	0.96			
5	0.17	0.03	1.00	0.13	0.02	0.98			
6				0.08	0.01	1.00			

Table 3 summarizes the contribution ratios and eigenvalues calculated using PCA procedure.

Table 4

Coefficient of Variables

Market-based		News-based		Social Media-based	
Variables	PC1	Variable	PC1	Variable	PC1
RIPO	0.51	*fdi_ns*	0.71	*FB*	0.55
NIPO	0,56	*pol_ns*	-0.70	*OLX*	0.30
TURN	0.52			*Youtube*	0.11
DP	-0.33			*Google*	0.54
EQI	0.17			*Twitter*	0.54
				Express	-0.05

Table 4 shows the coefficients of interest determined by PCA procedure.

4.2. Dependent variable

We have measured a variety of anomaly based sorted returns and used as dependent variables in this study. For the anomaly strategies, we follow the idea revealed by Stambaugh et al., (2012) and get the value-weighted returns of 1 to 10 decile of the anomaly's sorted variable for the period of 2009-2019. We use the short-, long-, and long minus short-leg strategies for the non-financial sectors. The short-leg (long-leg) reveals the lower-performing (higher-performing) decile.

5. Model specification

5.1. Investor sentiment and anomaly strategy

We offer the predictive regression model to observe whether the investor sentiment index predicts the anomalies sorted return, as shown in equations (6). We construct the long-short anomaly's strategies as revealed by Liu et al. (2019) to analyse the rich view of investor sentiment for the financial and non-financial sectors. We propose the following panel regression model.

$$r_{i,t} = \alpha + b_1 sent_{\mathrm{t}-1} + b_t \sum_{t=2}^{N} Z_{\mathrm{t}} + \varepsilon_t \qquad (6)$$

Where, $r_{i,t}$ is the anomaly's sorted excess return of individual stock *i* in time *t* on short-, long-, or the long minus short-leg while $sent_{t-1}$ is the news-, market-, and social media-based investor sentiment at time *t-1.* We also include some control variables Z_t in the baseline model to test the persistence of the investor sentiment. Subsequently, α and b are the coefficients of the interest of the model. We follow the idea revealed by Heston and Sinha (2017) and Sinha (2016) to observe the applicability of the investor sentiment for a long period.

5.2. Robustness check and subsample analysis

As a robustness check, we use the interaction term of market-, news-, and social media-based sentiment and its influence on the anomaly-based sorted excess return through panel regression. We test the panel regression model with market wide sentiment as can be seen in equations (7).

$$r_{i,t} = \alpha + b_1 MNB_{\mathrm{t}-1} + b_t \sum_{t=2}^{N} Z_{\mathrm{t}} + \varepsilon_t \qquad (7)$$

Where, $r_{i,t}$ is the anomaly's sorted excess return of individual stock *i* in time *t* on short-, long-, or the long minus short-leg while $sent_{t-1}$ is the interaction term of news-, social media, and market-based sentiment at time *t-1.* Furthermore, we examine the regression analysis using subsample analysis, where we utilize the cement industry and the same way to determine whether our results stay consistent.

5.3. Further analysis

We introduce the interaction term of news-, market-, and social media-based investor sentiment and see if the findings remain consistent. Equation (8) depicts the empirical model.

$$r_{i,t} = \alpha + b_1 sent_{t-1}^{B} * sent_{t-1}^{N} * sent_{t-1}^{M} + b_t \sum_{t=2}^{N} Z_{\mathrm{t}} + \varepsilon_t \qquad (8)$$

Where, $r_{i,t}$ denots the anomaly's sorted excess return of individual stock *i* in time *t* on short-, long-, or the long minus short-leg and $sent_{t-1}^{B} * sent_{t-1}^{N} * sent_{t-1}^{M}$ is the interaction term of market-, news-, and social media-based investor sentiment at time *t-1.*

6. Empirical findings and discussion

This segment summarizes the observations and discusses the anomaly strategies. Table 2 provides descriptive statistics for the monthly and quarterly indicators used in the empirical analysis. The average mean value of the sorted return of the short-leg and long-leg anomalies is positive except for the inventor turnover, sale and gross profit margin. The minimum value of anomalies' sorted returns begins with a negative number and the maximum value of the anomalies' sorted returns is positive as seen in Table 2.

6.1. Results

In this part, we present the regression results of anomaly strategies based on the method proposed by Stambaugh et al., (2012). In terms of news-wide sentiment, we see that our hypothesis predicts a negative relationship between each short-leg approach and news sentiment in the non-financial sector, as seen in Table 5. Overall, we see a strong predictive relationship between the short-leg strategy and news sentiment in the case of news based sentiment. Except for asset turnover, we detect a positive relationship between anomalies-based sorted return and news-based sentiment in the long-leg strategy, as shown at the top of Table 5. Likewise, we observe a negative relation between long-short strategy and news based sentiment except for the Asset turnover and gross profit margin as seen in the last column of Table5.

Our findings are consistent with those of Stambaugh et al., (2012), who found that an anomalous strategy can play a key role in determining stock performance. Furthermore, it demonstrates the significance of sentiment in stock trading strategies, as (Ding, Guo and Zhang, 2024) also argues that investor sentiment is unavoidable during the trading of initial public offerings (IPOs). All of this shows that news-based sentiment plays a significant predictive role in short, long and long-short strategies in the case of non-financial sector of Pakistani market. Our findings are consistent with (Funke and Matsuda, 2006) and (Stambaugh, Yu and Yuan, 2012)'s prior work, which found that anomaly strategy under the news sentiment has a key impact in determining return. Furthermore, traders may anticipate their long or short positions based on the news-based sentiment settings, which can result in an increased stock return.

Table 5

Anomaly strategies under new-based sentiment driven investors

$$r_{i,t} = \alpha + b_1 sent_{t-1} + b_t \sum_{t=2}^{N} Z_t + \varepsilon_t$$

	Short_Leg	*Long_Leg*	*Long-Short*
Anomaly	*B*	*B*	*B*
ATR	-0.671***	-0.022***	0.139***
	(0.102)	(0.001)	(0.008)
DEDT_I	-0.494***	0.177**	-0.118***
	(0.047)	(0.068)	(0.016)
WC	-0.280***	0.138***	-0.604***
	(0.083)	(0.003)	(0.026)
ITR	-0.879***	0.090***	0.381***
	(0.083)	(0.018)	(0.016)
SALE	-0.542***	0.244***	-0.142***
	(0.099)	(0.082)	(0.024)
ASTG	-0.261**	0.328***	-0.271***
	(0.119)	(0.091)	(0.018)
GPM	-0.632***	0.087***	0.050***
	(0.006)	(0.028)	(0.011)

Table 5 parades the regression results of anomaly strategies under news-based sentiment driven investor with some control variables. Standard errors are in parentheses

In the scenario of social media sentiment, all short leg strategies become negatively relevant except for the gross profit margin, as shown in the first column of Table 6. Furthermore, as seen in column 2 of Table 6, the long strategy under social media sentiment is positively significant.

Furthermore, the overall prediction outcome is negative in the case of long-short strategy under social media sentiment. The findings indicate that social media sentiments can predict short-leg, long-leg, and long-short strategies in the Pakistani stock market. Social media is recognized as an efficient informal information source that reduces the likelihood of a collision by directly or indirectly disseminating reliable information. (Ahn and Jung, 2024) emphasizes the importance of social media and points out that the quantity of videos and the probability of stock carnage are inversely correlated. Similarly, when employing the anomalous technique, our results demonstrate the importance of social media sentiment and its impact on stock performance.

Table 6

Anomaly strategies under social media –based sentiment driven investors with control

$$r_{i,t} = \alpha + b_1 sent_{t-1} + b_t \sum_{t=2}^{N} Z_t + \varepsilon_t$$

Anomaly	*Short_Leg* *B*	*Long_Leg* *β*	*Long-Short* *B*
ATR	-0.021***	0.004***	0.011***
	(0.007)	(5.10e-05)	(0.001)
DEDT_I	-0.046***	0.019***	-0.065***
	(0.008)	(0.006)	(0.002)
WC	-0.057***	0.025***	-0.041***
	(0.006)	(0.003)	(0.004)
ITR	-0.066***	0.008**	0.038***
	(9.16e-05)	(0.004)	(0.002)
SALE	-0.101***	0.048***	-0.008***
	(0.016)	(0.004)	(0.004)
ASTG	-0.027**	0.018***	-0.022***
	(0.008)	(0.004)	(0.002)
GPM	0.026	0.195***	0.606***
	(0.020)	(0.005)	(0.011)

Table 6 parades the regression results of anomaly strategies under social media-based sentiment driven investor with additional control variables. Standard errors are in parentheses

As seen in Table 7, anomaly strategies under market-wide investor sentiment are more predictive. As seen in columns 1 and 2 of Table 7, the short strategy under market wide investor sentiment is negatively significant, whereas the long strategy under market wide sentiment is positively significant. Furthermore, as seen in the last column of Table 7, the long-short strategy outperformed the market-wide sentiment. Table 7 shows that market sentiment also has a predictive role in the Pakistani market. (Ahmed, 2020) also emphasizes the relevance of market-based sentiment, and our findings show that market-wide sentiment is very essential in determining stock performance under anomaly techniques. Our findings are also consistent with the study by (Baker and Wurgler, 2006), which claims that the optimal trading strategy requires market sentiment. Furthermore, the study by (Stambaugh, Yu and Yuan, 2012) supports our findings, showing that long strategy is positively significant and short strategy is negatively significant.

Table 7

Anomaly strategies and market-based sentiment driven investors with control variables (Robustness Check)

$$r_{i,t} = \alpha + b_1 sent_{t-1} + b_t \sum_{t=2}^{N} Z_t + \varepsilon_t$$

	Short_Leg	*Long_Leg*	*Long-Short*
Anomaly	*B*	*β*	*B*
ATR	-0.136***	0.470***	0.016***
	(0.012)	(0.022)	(0.001)
DEDT_I	-0.117***	0.021**	0.020***
	(0.015)	(0.007)	(0.002)
WC	-0.147***	0.377***	0.138***
	(0.006)	(0.016)	(0.001)
ITR	-0.025***	0.008*	-0.056***
	(0.015)	(0.005)	(0.001)
SALE	-0.115***	0.033***	0.083***
	(0.012)	(0.005)	(0.002)
ASTG	-0.091**	0.195***	0.014***
	(0.015)	(0.036)	(0.002)
GPM	-0.186***	0.895***	0.081***
	(0.034)	(0.202)	(0.000)

Table 7 parades the regression results of anomaly strategies under market wide sentiment driven investor. Standard errors are in parentheses.

6.2. Robustness check and subsample analysis

We evaluate an interaction term of market-, news-, and social media-based investor sentiment and its influence on stock return under anomaly strategies as a robustness check. The combined sentiment has a significant negative influence on future stock performance in short-leg anomaly strategies. As shown in Table 8, the long-leg strategies have a positive relationship between combined sentiment and future anomaly-based sorted return, but the long-short strategy has a negative relationship with combined sentiment. In the Pakistani market, the combined sentiment term is strong and has a similar predictive role as can be seen in the Table 8.

Table 8

Anomaly strategies and sentiment driven investors (Robustness Check)

$$r_{i,t} = \alpha + b_1 MNB_{t-1} + b_t \sum_{t=2}^{N} Z_t + \varepsilon_t$$

	Short_Leg	*Long_Leg*	*Long-Short*
Anomaly	*B*	*B*	*B*
ATR	-0.018***	0.009***	-0.046***
	(0.001)	(0.002)	(0.004)
DEDT_I	-0.227***	0.076**	-0.261***
	(0.013)	(0.032)	(0.005)
WC	-0.015***	0.122***	-0.200***
	(0.033)	(0.039)	(0.013)

ITR	-0.027***	0.112***	-0.057***
	(3.72e-6)	(0.025)	(0.009)
SALE	-0.174***	0.149***	-0.214***
	(0.031)	(0.029)	(0.012)
ASTG	-0.028**	0.251***	-0.174***
	(3.38e-05)	(0.063)	(0.006)
GPM	-0.514***	0.056***	-0.263***
	(0.029)	(0.002)	(0.003)

Table 8 parades the regression results of anomaly strategies and interaction term of news-, market-, and social media-based sentiment driven investor. Standard errors are in parentheses.

Our subsample study, which includes the cement industry, confirms that anomalous approach is extremely relevant in the context of the Pakistani market, as shown in Table 9. The long-leg approach has a positive association with combined sentiment, but the short-leg techniques have a negative link with future anomaly-based sorted return.

Table 9

Anomaly strategies and sentiment driven investors (Subsample Analysis)

$$r_{i,t} = \alpha + b_1 Sent_{t-1} + b_t \sum_{t=2}^{N} Z_t + \varepsilon_t$$

	Short_Leg	*Long_Leg*	*Long-Short*
Anomaly	*B*	*B*	*B*
ATR	-0.136***	0.093*	-0.34***
	(0.025)	(0.054)	(0.095)
DEDT_I	-0.485***	0.050*	-0.572 ***
	(0.121)	(0.027)	(0.016)
WC	-0.013**	0.137***	0.047***
	(0.00)	(0.033)	(0.010)
SALE	-0.057***	0.083***	0.061***
	(0.032)	(0.019)	(0.016)
ASTG	-0.688***	0.142***	-0.651***
	(0.138)	(0.027)	(0.053)
GPM	-0.021	0.421***	-0.701***
	(0.034)	(0.062)	(0.005)

Table 9 parades the subsample regression results of anomaly strategies under news wide sentiment driven investor. Standard errors are in parentheses

6.3. Discussion

In this study, we examine the link between market, news, and social media sentiment and anomaly-based future stock returns. (Lupu *et al.*, 2022) has emphasized the significance of the anomaly, which alters the firm's risk factors and, as a result, the company's return. Our findings also show that traders may benefit from both short and long positions using anomalous strategies. All of the results from the multiple anomaly strategies support the significance of market-, news-, and social media-based sentiment in the Pakistani market. Our empirical findings are similar with prior research by Stambaugh et al. (2012), who investigate the effective influence of investor sentiment on the anomaly-based stock return. Overall, market, news, and social media sentiment have a significant negative influence on future stock returns in the case of short leg strategies while having a positive impact in the case of long leg strategies.

The method we used in our empirical analysis is the same as revealed by Stambaugh et al. (2012), and our findings are consistent with the prior work. In the context of the Pakistani market, we observed a significant negative impact of news-, social media-, and market-based sentiment on the short leg anomaly strategy while positive on the long leg strategy, implying that investors in the Pakistani market can earn more profit by incorporating such anomaly strategies. Baker and Wurgler (2006) and Huang et al. (2015) support our findings, demonstrating that sentiment has a considerable influence on future stock performance.

In this context, (Kumari, 2019) has also noted the correlation between investor sentiment and liquidity, specifically in the context of the Indian stock market, which is likewise an emerging market, while Pakistan is similarly an emerging economy, and we discovered a noteworthy correlation between investor sentiment and stock performance. Additionally, (Ding, Guo and Zhang, 2024) has investigated how news-based investor mood influences the Malaysian stock exchange, which is also an emerging economy. These findings corroborate our findings that investor sentiment is a critical component of both advanced and emerging economies. In the context of Pakistani stock markets, (Parveen *et al.*, 2020) has also examined the effects of overconfidence on trading volume, which lends credence to our research in which we have also found that investor sentiment affects stock performance under the anomaly strategies. In the meantime, (Xiao, Jiang and Zhang, 2024) further supports the link between sentiment and stock market volatility in the context of the Chinese stock market. Every piece of research demonstrates that irrational behavior is inevitable in trade operations, whether in industrialized or emerging economies. The literature backs up our findings and demonstrates that, under anomalous methods, sentiment based on news, markets, and social media can be used to manipulate the Pakistani stock market.

7. Conclusion

Sentiment from the market, news, and social media all have a role in forecasting trade activity. In this context, we assess sentiment using market-, news-, and social media-based proxies to investigate its impact on long-, short-, and long minus short-term strategies. To assess robustness, we examined a composite sentiment using market-, news-, and social media-based proxies, as well as its impact on anomaly-based future stock returns.

Our predictive regression results show that market, news, and social media sentiment have a substantial influence on long and short-term strategies in Pakistan's capital market. Social media, market, and news-based emotion have a large negative influence on future stock returns for short-leg anomaly strategies, but a positive impact on long-leg anomaly strategies.

Our empirical analysis is useful for both financial professionals and academics. This study reveals that investor sentiment is crucial for emerging economies, refuting the view that sentiment is primarily significant in develop countries. Regional and sector-specific comparisons may be one of the most relevant areas for future research.

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