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Full Length Article

The impact of investor sentiment on returns, cash flows, discount rates, and performance

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Abstract

Investor sentiment is believed to play an increasingly significant role in business and economic activities. By analyzing data collected from a sample of listed nonfinancial firms in Pakistan for the period 2009−2018, we quantify investor behavior and how it affects market returns, cash flows, discount rates, and firm performance. We find that investor sentiment has a significant impact on market activities, and our findings are in line with existing behavioral finance theories. Not only does our study offer theoretical confirmation of the significance of investor sentiment in aggregate market- and firm-level indicators, but it also offers new insights concerning market-based, news-based, and social media−based sentiment in the context of the Pakistani market.

JEL classification: G10; G14

Keywords: Cash flows; Discount rates; Firm performance; Investor sentiment; Market returns

1. Introduction

Why does investor sentiment matter? For more than two decades, this question has made the rounds of finance literature. Investor sentiment has not only been a heavily covered topic in finance literature (Park & Sohn, 2013) but also explains the financial decision-making process (Parveen et al., 2020), investor positions (Frazzini & Lamont, 2008), the sources of risk (Cagli et al., 2020), risk preferences (Qadan et al., 2019), and risk premiums (Qadan & Aharon, 2019).

Investor sentiment is inevitably considered because it surfaces existing stock market biases and opens up opportunities for earning abnormal returns by taking advantage of market bias (Fisher & Statman, 2013). Previous studies have documented the relationship between investor sentiment and the stock market (Schmeling, 2009). However, identifying and measuring investor sentiment and its impact on stock returns remains an area of interest regarding emerging economies. Different methods of measuring investor sentiment have been suggested, including market-based, survey-based, and news-based methods, as explored by Qadan and Aharon (2019). Petit et al. (2019) use a broad set of indirect and hidden information to examine investor sentiment whereas Baker and Wurgler (2006) use information on the real estate market to determine investor sentiment.

We use a sample of listed nonfinancial firms in Pakistan for the period 2009−2018. Our firm-specific, market-related, and news-related data come from the State Bank of Pakistan (SBP) and the Pakistan Stock Exchange (PSX). We construct market-, news-, and social media−based sentiment proxies and the partial least squares (PLS) and principal component analysis (PCA) approaches to measure investor sentiment, which are then used as separate independent variables. To obtain data for the news proxies, we take Bloomberg's comprehensive database and convert the data points into a news score using Python's Natural Language Tool Kit (NLTK) package. To

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construct variables for market sentiment, we use trading volume (*Tr_Vol*), market capitalization (*Mkt_Cap*), interest rate spread (*TED*), balance of trade (*BOT*), foreign exchange reserves (*FER*), and high minus low market-index (*HL_index*) proxies. Then, to quantify media–based investor sentiment, we use social media platforms, such as Facebook, YouTube, Offline Express Pakistan (OLX), Express, Google, Twitter, and porn webpage trend proxies. The aggregate market returns, aggregate cash flows (growth in the gross domestic product), discount rates, free cash flow, and stock returns are used as dependent variables.

In this study, we examine a question that is particularly relevant for emerging economies at both the academic and market level, which has not been explored before in the context of the Pakistani stock market. We use a simple time-series linear regression model to determine the relationship between investor sentiment and aggregate market levels. We use panel regression and the two-stage least squares (2SLS) method to perform a firm-level analysis. We find that investor sentiment has a significant impact on aggregate future market- and firm-level indicators, including returns, cash flows, discount rates, and firm performance. The novelty of the present study is its use of different sets of proxies to measure news-based, market-based, and social media–based investor sentiment separately in its empirical analysis. The results of our study confirm that investor sentiment is a contrarian predictor, and these results are, thus, in line with the findings of prior studies on this subject (Baker & Wurgler, 2006). This paper contributes to the literature on investor sentiment and how it affects market- and firm-level indicators. If investor sentiment has a significant impact on the decision-making process, as revealed by Parveen et al. (2020), then this sentiment may also have an impact on market- and firm-level indicators. None of the earlier studies focused on investor sentiment and its impact on overall market- and firm-level indicators across the board with respect to Pakistan's stock market.

The rest of the paper is structured as follows. In Section 2, we offer a brief overview the previous literature on this subject and propose our hypotheses. In Section 3, we discuss our research methodology and how we collected our data. In Section 4, we present our results and discussions. And in Section 5, we outline our conclusions.

2. Literature review and related hypothesis

2.1. Prior work on sentiment proxies

Previous studies have recorded the value of news and its effect on the public mood, markets, and business activities (Tetlock, 2007; Zhang et al., 2018) because it is the primary tool for attracting investor attention (Gountas et al., 2019). Investors divide news content based on whether it is good or bad (Depken, 2001). A strong association exists between economic news and the stock market (Birz & Lott, 2011). Similarly, social media has become a powerful tool for measuring the mood of investors that significantly affects the stock market (Nisar & Yeung, 2018), and market-based proxies are one of best-known proxies in finance. Huang et al. (2015) employ indicators for market-wide sentiment to explain stock performance. For example, market liquidity can be viewed as a good indicator of investor sentiment (Hsieh & Nguyen, 2020). As Hsieh and Nguyen (2020) have observed, market-wide economic policy uncertainty (EPU) has an important role in driving investor sentiment.

Sentiment can be affected by economic and non-economic events. Television, social media, and other media have a significant impact on people's moods (Lepori, 2015), and weather conditions also influence human psychology (Bassi et al., 2013). Consequently, Qadan and Aharon (2019), based on a survey-based questionnaire, propose that sentiment can also be derived from a non-economic event.

2.2. Investor sentiment and stock market outcomes

Emotions play a significant role in decision making (Kuhnen & Knutson, 2011) and increase the likelihood of investment in risky assets (Mickelson & Liston, 1990). Based on the state of the economy, investors become more optimistic about the stock market, believing in not only rational factors but also irrational factors, such as investor sentiment (Qadan & Aharon, 2019). Recent studies have suggested that investor sentiment explains the performance of financial securities. Thus, Çepni et al. (2020) examine the impact of investor sentiment on government bonds. Khan et al. (2019) use Google trend data to derive investor sentiment and predict US stock returns. Further, Sibley et al. (2016) confirm that investor sentiment based on economic fundamentals affects cross-sectional stock performance.

2.3. Hypothesis development

The overall purpose of this study is to validate the existence of investor sentiment and its impact on the stock market. We infer that media, news, and market indicators are important in financial markets. Huang et al. (2015) analyze the strong impact of investor sentiment on aggregate market performance using a PLS approach. We propose to test the following hypothesis:

Hypothesis 1. *Aggregate market returns tend to be affected significantly by investor sentiment.*

We also consider whether investor sentiment has a significant influence on aggregate cash flows, and so we propose a second hypothesis as follows:

Hypothesis 2. *Investor sentiment has a strong impact on aggregate cash flows.*

Huang et al. (2015) also examine the relationship between investor sentiment and future cash flows. To investigate the cross-sectional effects of these factors, we propose the following hypothesis:

Hypothesis 3. *An investor's emotions can have a significant impact on the cross-sectional returns.*

For a robustness check, we examine the impact of investor sentiment on firm-level variables, and, thus, we propose three more hypotheses, as follows:

Hypothesis 4. *Investor sentiment significantly influences firms' free cash flows.*

Hypothesis 5. *Investor sentiment is an important factor in predicting a firm's discount rate.*

Hypothesis 6. *Investor sentiment has a significant influence on firm efficiency.*

3. Research design

3.1. Sample selection

Our sample consists of data on nonfinancial firms listed in Pakistan from 2009 to 2018. We obtained macroeconomic data regarding gold reserves, the exchange rate, the government debt securities rate, special drawing rights (SDR), and the money supply from the SBP website. In some of the existing literature on this subject, other macroeconomic variables, such as inflation, interest, and money supply, are reviewed (Pearce & Roley, 1985; Rangel, 2011; Steeley, 2004). To measure investor sentiment, we use market-, media-, and news-based data. Foreign investment news (*fi_ns*) and political news (*pol_ns*) were obtained from the Bloomberg database.

Why do we use *pol_ns* and *fi_ns*? News on foreign investment is an important factor that may increase economic productivity (Altomonte & Pennings, 2009) and stimulate economic growth (Gunby et al., 2017; Shah et al., 2019). Similarly, as Al-Maadid et al. (2020) and Braga-Alves (2018) have pointed out, *pol_ns* affects stock prices. We also collected data regarding market-based proxies, such as *Tr_Vol*, *FER*, *Mkt_Cap*, *HL_index*, *TED*, and *BOT* from SBP and PSX. To obtain data for the social media-based proxies on Pakistan, we used social media platforms, such as Facebook, YouTube, OLX, Express, Google, and porn webpage trends, following Khan et al. (2019).

3.2. Variable definition and summary of statistics

The variable definitions used in our empirical analysis are presented in Table S1 (available online). Meanwhile, Table 1 shows the descriptive statistics for the data used in our empirical study on a monthly and quarterly basis. The mean of market sentiment (*M_Sent*) and social media sentiment (*MED_Sent*) are positive, but the mean of *N_Sent* is negative in the PLS approach as shown in Table 1. The value of sentiment is initially negative, and the maximum remains positive using both PLS and PCA. The average *DR* (0.172) and *ROE* (0.01) are positive, but *FCF* is negative (−0.581).

Overall, the average value of market-, news-, and social media−based proxies is positive, except for BOT and TED, as shown at the bottom of Table 1 (Column 2). The monthly and quarterly mean effects of firm-specific and macroeconomic variables are listed in Column 2. All the control variables have positive mean values with different standard deviations, as seen in Column 3. About half the coefficients of interest have a negative minimum, while the maximums for the control variables are positive, including for the firm-specific and macroeconomic variables.

Table 1
Descriptive statistics.

Variables	(1)	(2)	(3)	(4)	(5)
	N	Mean	Sd	Min	Max
Monthly Sentiment indicators					
FER	120	15,338	3808	6869	22,834
M3	120	1.204e+07	4.221e+06	5.768e+06	2.008e+07
TR_vol	120	1.076e+08	4.976e+07	0	2.060e+08
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
TED	120	−0.0004	0.005	−0.030	0.014
HL_Index	120	320.9	203.5	101.7	1109
Fdi_News	120	0.031	0.029	−0.065	0.101
Mkt_Ret	119	0.017	0.046	−0.085	0.222
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
M_Sent^{PCA}	120	4.47e-09	1.000	−1.077	3.875
N_Sent^{PCA}	120	3.41e-09	1.000	−2.390	5.346
MED_Sent^{PCA}	120	2.15e-09	1.000	−1.570	4.236
Quarterly Sentiment indicators					
M_Sent^{PLS}	40	2.63e-09	1.000	−1.076	5.939
N_Sent^{PLS}	40	−2.24e-09	1.000	−6.148	0.303
MED_Sent^{PLS}	40	4.10e-09	0.931	−1.196	2.388
Firm-specific indicators					
D/E	7343	4.053	24.42	0.001	795.7
ITR	7343	51.82	453.4	−0.289	12,836
LTB	7343	1.345e+06	4.297e+06	0	4.986e+07
LTI	7343	1.576e+06	8.549e+06	0	1.400e+08
Q/R	7343	1.158	10.63	0	274.0
RB	7343	585,652	4.864e+06	−8.494e+07	8.413e+07
SALES	7343	1.895e+07	7.192e+07	−476,405	1.190e+09
DR	7071	0.172	0.132	0.024	2.362
FCF	7343	−0.581	2.430	−46.59	1.912
ROE	7343	0.008	2.662	−109.4	12.50

Table 1 shows the data summary statistics. It shows pooled observations, such as the mean, statistical deviation, minimum, and maximum.

3.3. Model specification

3.3.1. Investor sentiment and aggregate-level indicators

Following Huang et al. (2015), we propose that investor sentiment significantly affects aggregate market returns and cash flows, as shown in Equations (1) and (2). We use a time-series regression to examine how investor sentiment affects aggregate future market returns and cash flows.

$$Mkt\_ret_t = \beta_0 + \beta_1 Sent_{t-1} + \gamma_t + \phi_t + \varepsilon_t \quad (1)$$

$$CF_t = \beta_0 + \beta_1 Sent_{t-1} + \gamma_t + \varepsilon_t \quad (2)$$

where Mkt_ret_t and CF_t are the aggregate monthly market returns and quarterly aggregate cash flows, respectively, and γ_t and ϕ_t are the monthly and yearly effects, respectively. In our regression model, we only use the first principal component as an indicator of investor sentiment.

3.3.2. Investor sentiment and cross-sectional returns

We propose that market-, news-, and social media–based investor sentiment is important in determining future stock returns, and Equation (3) summarizes the relationship between stock returns and investor sentiment.

$$r_{it} = \beta_0 + \beta_1 Sent_{t-1} + \varepsilon_{it} \quad (3)$$

Following Fama and French (1992), we constructed a monthly 5 × 5 portfolio of stocks that were weighted equally by their size and the book-to-market ratio, where r_{it} represents the excess return for each stock.

3.3.3. Investor sentiment and firm-level indicators (robustness check)

We propose that investor sentiment has a large effect on future discount rates, so we use the weighted average cost of capital as a proxy for the discount rate. For a robustness check, we examine whether investor sentiment affects stock returns (Baker & Wurgler, 2006), decision making (Parveen et al., 2020), liquidity premiums (Hsieh & Nguyen, 2020), size premiums (Qadan & Aharon, 2019), and aggregate-level indicators (Huang et al., 2015), which might suggest that it also affects firm-level indicators, such as future discount rates, firm performance, and free cash flows. We represent this as follows:

$$DR_{it} = \beta_0 + \beta_1 Sent_{t-1} + \beta_n \sum\nolimits_{n=2}^{N} Z_{it} + \lambda_t + \phi_t + \tau_t + \varepsilon_{it} \quad (4)$$

where DR_{it} is the discount rate of an individual firm i at time t. Subsequently, we use a set of control variables Z_{it} (firm-specific and macroeconomic) as shown in Equation (4). Thereafter, λ_t, ϕ_t, τ_t, and ε_{it} show the quarterly-, yearly-, and firm-specific effects and error terms of firm i at time t, respectively.

Moreover, investor opinion might significantly influence the future cash flows of an individual company. The empirical model used to calculate it is as follows:

$$FCF_{it} = \beta_0 + \beta_1 Sent_{t-1} + \beta_n \sum\nolimits_{n=2}^{N} Z_{it} + \lambda_t + \phi_t + \tau_t + \varepsilon_{it} \quad (5)$$

where FCF_{it} represents the leveraged free cash flows of firm i at time t along with the set of control variables Z_{it}. We also evaluate the effect of investor sentiment on a firm's future performance using ROE as a proxy for performance. This can be represented as follows:

$$ROE_{it} = \beta_0 + \beta_1 Sent_{t-1} + \beta_n \sum\nolimits_{n=2}^{N} Z_{it} + \lambda_t + \phi_t + \tau_t + \varepsilon_{it} \quad (6)$$

where ROE_{it} is the return on equity, which shows the performance of firm i at time t. Likewise, Z_{it} represents a set of control variables (firm-specific and macroeconomic) in the model.

3.3.4. Endogeneity issue related to firm-level indicators

Further, we employ an instrumental variable–based approach to eliminate endogeneity from the model. We identified an instrument that is related to investor sentiment but not to the stock market index. Investment flows and political stability are essential factors in analyzing a country's economic conditions, which can also influence firms' activities. Flows of investment and political stability are related to investor sentiment. In this regard, we employ a two-stage least squares estimation. In the first stage, we regress lagged investor sentiment on the instruments along with a set of control variables. After obtaining the fitted value of $\widehat{Sent}$ in the first stage, we regressed the variables of interest (future firm performance, future discount rates, and future free cash flows) on $\widehat{Sent}$ along with all the control variables excluding the instruments used in the first stage. This can be represented as follows:

$$Sent_t = \gamma Z + \delta CV + u_{it} \quad (7)$$

$$Q_{itj} = \widehat{\beta Sent}_{t-1} + \delta CV + v_{it} \quad (8)$$

where Q_{itj} and $\widehat{Sent}_{t-1}$ (market, news, and social media) are the variables of interest j (discount rate, firm performance, and free cash flows) of individual firm i at time t and predicted investor sentiment, respectively. Z, CV, u_{it}, and v_{it} are the instruments, control variables, and error terms of the model, as shown in Equations (7) and (8).

4. Methods for measuring variables

4.1. Measuring proxies for sentiment

4.1.1. News-based proxies

We used the Bloomberg database to collect *fi_ns* and *pol_ns* for Pakistan over the period 2009–2018. Previous studies, such as those by Funke and Matsuda (2006) and Tetlock (2007), have used various methods, such as word count and algorithms, to measure the news data. We adopted the sentiment lexicon approach and used the VADER[1] dictionary along with the NLTK[2] package to classify sentiment, as proposed by Hutto and Gilbert (2014). This innovative methodology allowed us to determine positive and negative word polarity. The process of measuring textual information can be divided into the following steps: (1) initial text screening, (2) splitting the text into individual words, (3) removing stop words, (4) elimination of punctuation, (5) measurement of news-level

[1] Valence Aware Dictionary for Sentiment Reasoning.

[2] Natural Language Toolkit.

valence-based sentiment polarities (positive, negative, and compound polarities). For more detail, see the Supplementary Material (available online). Finally, we combined the positive and negative news polarity of the entire document and divided the difference in polarity by the compound polarity of the entire content. So, all our *fi_ns* and *pol_ns t* file-level sentiment scores are measured as shown in Equations (9) and (10), respectively.

$$fi\_ns_t = \frac{pos_t - neg_t}{comp_t} \tag{9}$$

$$pol\_ns_t = \frac{pos_t - neg_t}{comp_t} \tag{10}$$

where pos_j, neg_j, and $comp_j$ show the positive, negative, and compound polarity, respectively, of all the news content released on a specific day. Calomiris and Mamaysky (2019) used the same process, which involved finding the article-level sentiment score using a positive and negative sentiment word list. In this study, the news score is the key element used to determine the sentiments about an article. We also used the quarterly news score to determine the quarterly sentiment by taking the quarterly average of news-related sentiments. Previous literature on this subject indicates that long-horizon aggregate news does a better job of predicting stock market outcomes (Heston & Sinha, 2017). In this regard, we also examine the long-term impact of investor sentiment on market activities.

4.1.2. Market-based proxies

We collected the market-based proxies' (*FER, BOT, M3, TED, HL_index, Tr_Vol, and Mkt_Cap*) data for the period 2009–2018 from SBP and PSX.

4.1.3. Social media-based proxies

We used the trends on social media,[3] including Facebook, YouTube, OLX, Express, Google, Twitter, and porn videos, to see how widespread the use of the word "Pakistanis" was over a period of ten years, from 2009 to 2018, following the approach of Khan et al. (2019). We collect the monthly trends in social media in the first step and then use PCA to derive social media-based investor sentiment.

4.2. Measurement of the independent variable

Investor sentiment is the independent variable with regard to average monthly market-based, news-based, and social media-based data. We used a different set of sentiment proxies to measure investor sentiment, with the same method as the one used by Baker and Wurgler (2006) and Huang et al. (2015). However, we used a different set of proxies to construct investor sentiment and obtained the results using both PCA and PLS (see Table S2, available online). Investor sentiment is defined in Equations (11)–(13) using this information (see Table S3, available online). We present only the PCA coefficients and not the equations underlying the PLS approach, but they can be calculated using the same method.

$$\begin{aligned} M\_Sent_t = {} & 0.17(Mkt\_Cap)_t + 0.57(Tr\_vol)_t - 0.22(HL\_index)_t \\ & + 0.03(TED)_t + 0.59(M3)_t - 0.42(BOT)_t \\ & + 0.21(RES)_t \end{aligned} \tag{11}$$

$$N\_Sent_t = -0.71(Pol\_ns)_t + 0.7(fdi\_ns)_t \tag{12}$$

$$\begin{aligned} MED\_Sent_t = {} & 0.52(FB)_t + 0.21(OLX)_t + 0.04(Por)_t \\ & - 0.30(Youtube)_t + 0.15(Google)_t \\ & + 0.53(Twitter)_t + 0.52(Express)_t \end{aligned} \tag{13}$$

where *M_Sent* = market-based sentiment, *N_Sent* = news-based sentiment, and *MED_Sent* = social media–based sentiment. Only the first principal component is used as a measure of investor sentiment, and it has a linear relationship with the original collection of proxies.

4.3. Measurement of dependent variables

In this study, we consider a variety of variables of interest. Aggregate market returns and individual stock returns are the difference between the index and stock values on the current day and the index and stock values on the previous day, divided by the previous day's index and stock values, as shown in Equations (14) and (15).

$$Mkt\_Ret_t = (Mkt\_index_t - Mkt\_index_{t-1})/Mkt\_index_{t-1} \tag{14}$$

$$r_{it} = (p_{it} - p_{it-1})/p_{it-1} \tag{15}$$

Meanwhile, following Huang et al. (2015), who examine the impact of investor sentiment on aggregate-level indicators, we use GDP growth as a measure of the aggregate cash flows by the country. Aggregate cash flow is the difference between GDP on the current day and on the previous day, divided by the previous day's GDP, as shown in Equation (16). In the following equations, i and t denote individual stocks and time, respectively.

$$CF_t = (GDP_t - GDP_{t-1})/GDP_{t-1} \tag{16}$$

The discount rate is calculated using the weighted average cost of capital, combining the cost of debt and the cost of equity. We measure the cost of equity using the capital asset pricing model (CAPM), and we estimate the cost of debt using the cost of interest from the income statements of individual firms. The weighted average cost of capital is used as a proxy for the discount rate, and the calculation is shown in Equation (17).

$$DR_{it} = (We{*}Ke)_{it} + (Wd{*}Kd)_{it}(1-T) \tag{17}$$

We include ROE to test firm performance, calculated by dividing net income by shareholders' equity as shown in Equation (18).

[3] https://trends.google.com.pk.

Table 2
Investor Sentiment, aggregate market return and cash flow.

Variables	Market-Based		News-Based		Social Media-Based	
	PCA-Based	*PLS-Based*	*PCA-Based*	*PLS-Based*	*PCA-Based*	*PLS-Based*
Panel A: Aggregate Market Return						
$Sent_{(t-1)}$	−0.010**	−0.011*	−0.022**	−0.027**	−0.010	−0.042*
	(0.004)	(0.005)	(0.013)	(0.009)	(0.013)	(0.021)
Cons.	0.042***	0.020**	0.050***	0.066***	0.061***	0.056***
	(0.015)	(0.009)	(0.017)	(0.021)	(0.016)	(0.014)
Month	No			Yes		
Year				Yes	Yes	Yes
Obs.	119	39	39	119	119	39
R^2	0.16	0.13	0.56	0.32	0.18	0.50
Panel B: Aggregate Cash Flow						
$Sent_{(t-1)}$	−0.071**	−0.0068*	−0.011***	−0.0064*	−0.005*	−0.011**
	(0.040)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)
SDR	−7.87e-06	−0.003			1.69e-06	
	(7.76e-06)	(0.004)			(7.74e-06)	
Inf				0.0014		
				(0.001)		
Gold			2.24e-05***	0.0001		9.84e-06**
			(6.25e-06)	(0.0001)		(4.68e-06)
$Gold_{(t-1)}$					1.21e-05***	
					(3.75e-06)	
Ex_Rate	−0.001				0.001***	
	(0.001)				(0.0003)	
Cons.	−0.039	0.025		−0.021	−0.123***	0.010
	(0.093)	(0.026)		(0.018)	(0.033)	(0.012)
Quarter	Yes		No		No	
Year	Yes	Yes		Yes		
Observations	35	35	35	35	35	35
R-squared	0.84	0.83	0.33	0.85	0.66	0.23

Table 2 reviews the effect of investor sentiment on the aggregate market return and cash flow in principal component and partial least squares analyses over the period 2009−2018. *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively.

$$ROE_{it} = \left(\frac{Net\ Income_{it}}{shareholder's\ equity_{it}}\right) \tag{18}$$

To calculate leveraged free cash flows, we used the difference between the cash flow from operations and investment in operating capital, as seen in Equation (19).

$$FCF_{it} = Cash\ flow\ from\ operation_{it} - Investment\ in\ operating\ capital_{it} \tag{19}$$

5. Empirical findings and discussion

5.1. Investor sentiment and aggregate-level indicators

We first determine the causality in the relationship between investor sentiment and aggregate-level indicators (see Table S4, available online). Consistent with the theory, the investor sentiment is a negative predictor: market-, news-, and social media-based sentiment have a negative impact on aggregate future market returns and estimated coefficients are [-0.010], [-0.022], and [-0.010], respectively. However, the estimated coefficients are different. News-based sentiment has the leading negative impact [-0.022] and economically, which means a one-standard-deviation increase in news-based sentiment is associated with a −2.2% decrease in expected excess market return for the next period. When we use other approaches we get similar results, as seen at the top of Table 2 (Panel A). Subsequently, the market-, news-, and social media-based sentiment have a negative impact on aggregate future cash flow and estimated coefficients are [-0.071], [-0.006], and [-0.005], respectively. The predicted coefficients, however, vary. The most negative effect is from market-based sentiment [-0.071] in PCA approach, which means that a one-standard-deviation increase in market-based sentiment decreases aggregate future cash flow by 7.1%. When we use PLS approaches we get similar results, as seen at middle of Table 2 (Panel B). As a consequence, we find that under the PCA technique, investor sentiment influenced by news has a larger predictive ability for aggregate future market return, whereas investor sentiment influenced by market has a better predictive ability for aggregate future cash flow. *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively. Standard errors are in parentheses. Aggregate-level indicators and investor sentiment behavior are presented graphically (see Fig. S7, available online).

Table 3
Investor sentiment and firm level indicators (robustness check).

Variables	Market-Based			News-Based			Social Media-Based		
	FCF	*ROE*	*DR*	*FCF*	*ROE*	*DR*	*FCF*	*ROE*	*DR*
Panel A:Principal Component Analysis-Based Results									
$Sent_{(t-1)}$	−0.031**	−0.010*	−0.007***	−0.011*	−0.077***	−0.016	−0.002	−0.005*	−0.002
	(0.014)	(0.062)	(0.001)	(0.006)	(0.298)	(0.011)	(0.035)	(0.032)	(0.001)
SALE	−8.37e-09***	5.44e-10			1.19e-09		−9.93e-09***	−1.72e-09	
	(9.50e-10)	(1.76e-09)			(1.78e-09)		(6.34e-10)	(1.77e-09)	
ATR	0.255***			0.00577			0.280***	0.634***	
	(0.042)			(0.00777)			(0.0388)	(0.0758)	
RB	−5.47e-08***	1.05e-08		−2.76e-08***	8.62e-09		−1.04e-07***	1.14e-08	
	(5.28e-09)	(9.94e-09)		(1.49e-09)	(9.90e-09)		(5.13e-09)	(9.88e-09)	
QR	0.001	0.005*		6.29e-05	0.005*		0.002	0.006**	
	(0.002)	(0.003)		(0.001)	(0.003)		(0.002)	(0.003)	
ITR		−9.60e-06	−1.02e-06		−2.10e-05	−4.31e-06*			−3.64e-07
		(6.83e-05)	(2.79e-06)		(6.80e-05)	(2.53e-06)			(2.81e-06)
D/E			0.001***			0.001***			0.001***
			(6.17e-05)			(5.46e-05)			(6.20e-05)
NPM			1.84e-06			−6.22e-08			2.04e-06*
			(1.23e-06)			(1.11e-06)			(1.24e-06)
NN2				0.002*					
				(0.001)					
Ex_Rate				−0.006*		−0.001			
				(0.003)		(0.001)			
$FCF_{(t-1)}$				0.970***					
				(0.00327)					
Gold	−4.86e-05	8.18e-05	1.46e-05***		4.60e-05		4.60e-06		
	(3.49e-05)	(6.39e-05)	(2.72e-06)		(0.000158)		(9.05e-05)		
SDR	0.0004***		0.0001***				−9.29e-07		0.0001***
	(5.83e-05)		(4.44e-06)				(9.57e-05)		(4.16e-06)
FER								−0.323***	
								(0.109)	
Cons.	−0.635***	−0.016	0.069***	0.418*	0.346	0.278***	−0.430**	2.476**	0.098***
	(0.222)	(0.414)	(0.017)	(0.254)	(0.503)	(0.047)	(0.214)	(1.130)	(0.016)
Firm	No	No	Yes		No			No	Yes
Sector				No					
Year				No	No	Yes	No		
Quarter									
Observations	7114	7114	6848	7112	7114	6848	7114	7114	6848
R^2	0.77	0.14	0.53	0.96	0.15	0.25	0.46	0.15	0.52
Panel B:Partial Least Square-Based Results									
$Sent_{(t-1)}$	−0.031**	−0.002	−0.007***	−0.022	−0.0001	−0.002	−0.001	−0.017	−4.90e-05
	(0.014)	(0.026)	(0.001)	(0.014)	(0.029)	(0.001)	(0.016)	(0.025)	(0.001)
SALE	−8.37e-09***	3.96e-10			1.19e-09		−9.93e-09***	−2.11e-09	
	(9.50e-10)	(1.75e-09)			(1.78e-09)		(6.34e-10)	(1.76e-09)	
ATR	0.255***			0.175***			0.280***	0.632***	
	(0.0416)			(0.040)			(0.0388)	(0.0760)	
RB	−5.47e-08***	1.08e-08		−6.48e-08***	9.01e-09		−1.04e-07***	1.14e-08	
	(5.28e-09)	(9.94e-09)		(5.13e-09)	(9.90e-09)		(5.13e-09)	(9.89e-09)	
QR	0.001	0.005*		0.001	0.005*		0.002	0.007**	
	(0.002)	(0.003)		(0.002)	(0.002)		(0.002)	(0.002)	
ITR		−8.09e-06	−1.02e-06		−2.08e-05	−1.25e-06			−4.34e-06*
		(6.83e-05)	(2.79e-06)		(6.81e-05)	(2.63e-06)			(2.53e-06)
D/E			0.001***			0.001***			0.001***
			(6.17e-05)			(5.83e-05)			(5.42e-05)
NPM			1.84e-06			1.09e-06			−5.76e-08
			(1.23e-06)			(1.16e-06)			(1.11e-06)
Ex_Rate	−0.018***		−0.005***						
	(0.002)		(0.0001)						
Gold	−4.86e-05	0.0001*	1.46e-05***				3.81e-06		−6.80e-06
	(3.49e-05)	(6.22e-05)	(2.72e-06)				(8.96e-05)		(5.98e-06)
SDR	0.0004***		0.0001***				−7.17e-07		
	(5.83e-05)		(4.44e-06)				(9.57e-05)		

(*continued on next page*)

Table 3 (*continued*)

Variables	Market-Based			News-Based			Social Media-Based		
	FCF	*ROE*	*DR*	*FCF*	*ROE*	*DR*	*FCF*	*ROE*	*DR*
FER								−0.256** (0.0994)	
Cons.	−0.635*** (0.222)	−0.071 (0.412)	0.069*** (0.017)	1.344*** (0.271)	0.321 (0.503)	0.734*** (0.018)	−0.426** (0.205)	1.823* (1.049)	0.240*** (0.014)
Firm	No	No	Yes	No	No	Yes		No	
Sector									
Year					No			No	Yes
Quarter									
Observations	7114	7114	6848	7114	7114	6848	7114	7114	6848
R^2	0.77	0.14	0.53	0.77	0.15	0.58	0.46	0.15	0.25

Table 3 shows the effect of investor sentiment on firm-level indicators, such as free cash flow, firm performance, and the discount rate. *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively. Standard errors are in parentheses.

5.2. Investor sentiment and cross-sectional returns

Overall, investor sentiment has a statistically significantly negative impact on cross-sectional future returns both with PCA and PLS approaches (see Table S5, available online). We constructed size-, and value-based portfolio strategies in which many strategies are significant in either the lower or upper quartile. However, market-wide sentiment is irrelevant with the PLS method (see Table S5, available online). Some strategies show a positive effect of lagged investor sentiment, but many of these strategies are better at capturing the negative effect of lagged investor sentiment. As a result, we conclude that investor sentiment based on news and social media has a better predictive ability of cross-sectional return than market sentiment. We also contend that the most attractive portfolio strategy can be found in either the lower or upper quartiles of size-, and value-based portfolio strategies.

5.3. Investor sentiment and firm-level indicators (robustness check)

For the robustness check, we examine the impact of investor sentiment on the firm's level indicators. Market related sentiment has a negative impact on the firm's future cash flow, return on equity, and discount rate, with estimated coefficients of [-0.031], [-0.010], and [-0.007], respectively. Consequently, news-based sentiment has a negative effect on the firm's future cash flow, return on equity, and discount rate, with estimated coefficients of [-0.011], [-0.077], and [-0.016], respectively. Subsequently, we also observe a negative effect of social media sentiment on the firm's future cash flow, return on equity, and discount rate, with estimated coefficients of [-0.002], [-0.005], and [-0.002], respectively, as seen at the top of Table 3 (Panel A). The discount rate coefficient, on the other hand, is insignificant. In general, using PLS methods produces similar but insignificant results, as seen in the middle of Table 2 (Panel B). As a result, we argue that the insignificance could be due to the endogeneity problem, and we present the results after addressing the endogeneity in the next section. *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively. Standard errors are in parentheses.

5.3.1. Endogeneity issue related to firm-level indicators

The coefficients are improved by using IVs and the Table S6 shows the results of the first-stage least squares regression (available online). In the second stage least squares regression results, market sentiment has a direct negative effect on the firm's future cash flow, return on equity, and discount rate, with estimated coefficients of [-0.074], [-0.050], and [-0.058] respectively. Thus, the effect of news-based sentiment on the firm's future cash flow, return on equity, and discount rate is negative, with estimated coefficients of [-0.010], [-0.039], and [-0.010] respectively. Next, We find that social media sentiment has a negative effect on the firm's future cash flow, return on equity, and discount rate, with estimated coefficients of [-0.014], [-0.010], and [-0.053], as seen at the top of Table 4 (Panel A). After addressing the endogeneity problem, the most negative effect is from market-based sentiment, which means that a one-standard-deviation increase in market-based sentiment decreases a firm's future cash flow, return on equity, and discount rate by 7.4%, 5%, and 5.8%, respectively. In addition, we use PLS approaches and get similar results, as seen at the middle of Table 4 (Panel B). As a result, we contend that investor sentiment based on market is more predictive, even at the firm level, than news or social media sentiment. *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively. Standard errors are in parentheses.

5.4. Discussion

In our research, we study investor sentiment and its impact on market- and firm-level indicators. Our findings are consistent with a previous study by Huang et al. (2015), which shows that investor sentiment negatively influences the aggregate future market return and future cash flows. In strategies with an equally weighted portfolio, overall market-, news-, and social media—based investor sentiment has a negative impact with size- and value-based strategies, as shown by Qadan and Aharon (2019) and Fama and French (1992), who highlight the importance of size and value in portfolio strategies. We find a bidirectional effect of investor sentiment on portfolio returns in some cases, which might be a

Table 4
Two-stage least squares regression results for the firm level indicators.

Variables	Market-Based			News-Based			Social Media-Based		
	FCF	*ROE*	*DR*	*FCF*	*ROE*	*DR*	*FCF*	*ROE*	*DR*
Panel A:Principal Component Analysis-Based Results									
$Sent_{(t-1)}$	−0.074***	−0.050***	−0.058***	−0.010*	−0.039***	−0.019**	−0.014***	−0.010**	−0.053***
	(0.022)	(0.017)	(0.004)	(0.006)	(0.012)	(0.008)	(0.002)	(0.005)	(0.002)
SALE		1.47e-10					−1.05e-09***	−7.05e-11	
		(1.80e-10)					(6.25e-11)	(8.81e-11)	
ATR	0.003			0.006			0.037***	0.046***	
	(0.005)			(0.008)			(0.003)	(0.005)	
RB	−6.71e-09***	8.34e-10		−2.80e-08***	3.29e-10*		−1.04e-08***	1.45e-09*	
	(5.18e-10)	(9.98e-10)		(1.52e-09)	(1.71e-10)		(5.15e-10)	(8.60e-10)	
QR	0.0001	0.001**		6.17e-05	−6.61e-05		0.0001	0.001**	
	(0.0001)	(0.0002)		(0.0004)	(5.00e-05)		(0.0001)	(0.0002)	
ITR		−1.94e-06	−2.97e-06		4.96e-07	−1.45e-06			−1.39e-07
		(6.84e-06)	(2.57e-06)		(1.17e-06)	(1.18e-06)			(2.82e-06)
D/E		−1.94e-06	−2.97e-06		4.96e-07	−1.45e-06			−1.39e-07
		(6.84e-06)	(2.57e-06)		(1.17e-06)	(1.18e-06)			(2.82e-06)
NPM			1.90e-07			3.33e-08			3.08e-06**
			(1.13e-06)			(5.01e-07)			(1.24e-06)
NN2				0.002					
				(0.001)					
Ex_Rate	0.001		−0.004***	−0.005*		0.001**			
	(0.001)		(0.0002)	(0.003)		(0.0003)			
$ROE_{(t-1)}$					0.974***				
					(0.002)				
$DR_{(t-1)}$						0.904***			
						(0.004)			
$FCF_{(t-1)}$				0.969***					
				(0.003)					
Gold	−1.65e-05***	−3.22e-06	1.83e-05***		6.38e-06**	−3.88e-05***	1.36e-05***	1.21e-05*	8.11e-05***
	(5.63e-06)	(7.91e-06)	(2.57e-06)		(2.79e-06)	(3.52e-06)	(4.16e-06)	(7.37e-06)	(3.13e-06)
Inf	0.002*					0.002***			
	(0.001)					(0.001)			
Cons.	−0.029	0.030	0.544***	0.438*	−0.015*	0.008	−0.111***	−0.087***	−0.047***
	(0.048)	(0.043)	(0.021)	(0.266)	(0.009)	(0.031)	(0.012)	(0.021)	(0.010)
Firm	No	No	Yes		No				
Sector				No					
Year				No	No	No			
Obs.	7112	7112	6846	6881	6881	6597	7112	7112	6846
R^2	0.77	0.14	0.60	0.96	0.97	0.87	0.45	0.01	0.13
Panel B:Partial Least Square-Based Results									
$Sent_{(t-1)}$	−0.068***	−0.053***	−0.107***	−0.057*	−0.196**	−0.106***	−0.064*	−0.017***	−0.035***
	(0.010)	(0.018)	(0.016)	(0.029)	(0.090)	(0.010)	(0.035)	(0.006)	(0.007)
SALE	−7.06e-10***	1.49e-10			3.08e-10		−1.07e-09***	−0.0001	1.28e-10**
	(1.00e-10)	(1.80e-10)			(2.16e-10)		(6.25e-11)	(8.87e-11)	(6.51e-11)
ATR	0.011**			0.009			0.038***	0.040***	
	(0.005)			(0.005)			(0.003)	(0.006)	
RB	−5.73e-09***	8.23e-10		−6.67e-09***	1.12e-10		−1.04e-08***	1.34e-09	
	(5.31e-10)	(9.98e-10)		(5.24e-10)	(1.09e-09)		(5.17e-10)	(8.59e-10)	
QR	0.0001	0.0005**		0.0001	0.001**		0.0001	0.001**	
	(0.0001)	(0.0002)		(0.0001)	(0.0002)		(0.0001)	(0.0002)	
ITR		−1.99e-06	−3.43e-06		−2.59e-06	−2.66e-06			−1.96e-06
		(6.84e-06)	(2.58e-06)		(6.88e-06)	(2.58e-06)			(2.57e-06)
D/E			0.001***			0.001***			0.001***
			(5.55e-05)			(5.73e-05)			(5.74e-05)
NPM			1.74e-08			1.98e-07			1.91e-07
			(1.14e-06)			(1.14e-06)			(1.13e-06)
Gold	−1.23e-05***	−2.94e-06	6.64e-06	4.02e-06	2.12e-05***	3.96e-05***	8.98e-06*	6.31e-06	3.33e-05***
	(4.02e-06)	(7.85e-06)	(4.53e-06)	(3.87e-06)	(7.78e-06)	(2.51e-06)	(4.88e-06)	(6.27e-06)	(2.73e-06)
RES								−0.036***	
								(0.010)	

(*continued on next page*)

Table 4 (*continued*)

Variables	Market-Based			News-Based			Social Media-Based		
	FCF	*ROE*	*DR*	*FCF*	*ROE*	*DR*	*FCF*	*ROE*	*DR*
Inf									0.0001
									(0.001)
M_Spy									−0.221***
									(0.026)
SDR									3.43e-06
									(5.65e-06)
Ex_Rate			−0.002***	−0.001		−0.003***		−0.001***	0.002***
			(0.0004)	(0.001)		(0.0002)		(0.0003)	(0.001)
Cons.	0.008	0.029	0.408***	0.042	−0.043	0.436***	−0.097***	0.443***	3.505***
	(0.024)	(0.043)	(0.033)	(0.056)	(0.044)	(0.027)	(0.013)	(0.107)	(0.366)
Firm	No	No		No	No	Yes			Yes
Sector									
Year							No		Yes
Obs.	7112	7112	6846	7112	7112	6846	7112	7112	6846
R^2	0.77	0.14	0.23	0.77	0.14	0.60	0.45	0.01	0.60

Table 4 shows the 2SLS regressions results. *, **, and *** indicate 1%, 5%, and 10% significance levels, respectively. Standard errors are in parentheses.

complicated reality; Qadan et al. (2019) observe a bidirectional (positive and negative) relationship between volatility and returns in the presence of investor sentiment. However, Hsieh and Nguyen (2020) find a positive impact of sentiment on liquidity premiums. In the Pakistani market, we find a significantly negative impact of investor sentiment on firm-level indicators, such as free cash flows, returns on equity, and discount rates. Our results are supported by previous studies (Baker & Wurgler, 2006; Huang et al., 2015), which show that investor sentiment has a significantly negative impact on future stock performance.

6. Conclusion

In this study, we examine the impact of market-, news- and social media–based investor sentiment on market activities. We analyze the effect of investor sentiment on aggregate-, market-, and individual firm–level indicators using the principal component analysis and partial least squares approaches.

Our study demonstrates that investor sentiment negatively affects aggregate future market returns and cash flows. Similarly, investor sentiment negatively affects cross-sectional future stock returns, free cash flows, firm performance, and discount rates in the Pakistani context. Our study contributes to knowledge about investor sentiment based on the market, news, and social media in Pakistan, which has not been explored before. Our findings apply as well to similar countries in Asia or elsewhere.

Our findings lead to the following commonsense tips. Understanding how investor sentiment affects financial performance may provide insights into the aggregate market- and firm-level functioning of the financial system. Our findings are also significant for researchers who use different proxies in different fields to measure investor sentiment. Further, our findings negate the general belief in previous literature that investor sentiment has a weak role in the investment markets of emerging economies. Our results are consistent with prior finance literature and provide concrete evidence that investor sentiment can be captured via news, market, and social media, which can be used to predict returns, cash flows, and firm performance. Overall, in the context of the Pakistani stock market, market-based sentiment has greater predictive ability at the aggregate and firm levels than news- and social media-based sentiment, and investors can use market-wide sentiment as a powerful common factor to forecast the stock market.

However, our research has some limitations concerning the collection of firm-specific and news data in Pakistan. Nevertheless, this study points to possible future directions of research. For example, it would be interesting to see how investor sentiment affects the operational, financial, and investment activities in a particular region and examine the impact of investor sentiment on small businesses, financial and nonfinancial firms.

Declaration of competing interest

There is no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2021.06.005.

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