5 GAUGING THE EFFECT OF INVESTOR SENTIMENT ON CRYPTOCURRENCY MARKET: AN ANALYSIS OF BITCOIN CURRENCY

Muhammad MOHSIN[1]
Sobia NASEEM[2]
Larisa IVAȘCU[3]
Lucian-Ionel CIOCA[4]
Muddassar SARFRAZ[5]
Nicolae Cristian STĂNICĂ[6]

Abstract

The advocates of classical finance rebuffed investors' sentiment, but some behavioral finance researchers highlight the effects of sentiments on investments and asset pricing. Primarily this research measured the investors' sentiments relationship with Bitcoin returns by using the market data proxy approach. We construct a sentiment index that compressed five renowned sentiment proxies based on the principal component analysis. Regression analysis is used to check the relationship between investor sentiment and Bitcoin returns. The results demonstrate that the coefficient of sentiment index behaves positively significant at the level of 5%. This study also concludes that the constructed sentiment index fits the market data proxy approach and improves Bitcoin prediction through an empirical test for its reasonability.

Keywords: Bitcoin returns; investor sentiment index; money flow index; Bitcoin index turnover; cryptocurrency market; financial market
JEL Classification: G4, G41, P34

[1] *School of Business, Hunan University of Humanities, Science and Technology, Hunan, PR China. Email; mohsinlatifntu@gmail.com.*
[2] *School of Economics and Management, Shijiazhuang Tiedao University, Shijiazhuang, Hebei, PR China. Email; Sobiasalamat4@gmail.com*.
[3] *Department of Management, Faculty of Management in Production and Transportation, Politehnica University of Timisoara, Timisoara, Romania; larisa.ivascu@upt.ro*.
[4] *Department of Industrial Engineering and Management, Faculty of Engineering, Lucian Blaga University of Sibiu, Romania. Email; lucian.cioca@ulbsibiu.ro*.
[5] *Binjiang College, Nanjing University of Information Science and Technology, Wuxi Jiangsu, PR China. Email:* muddassar.sarfraz@gmail.com. Corresponding author.
[6] *National Commission for Strategy and Prognosis. E-mail: cristian.stanica@cnp.ro*

1. Introduction

Investor sentiment leads towards investment risks and future cash flows, which cannot be justified by technical analysis. It raises curiosity and a newfangled area of debate for the researchers (Baker & Wurgler, 2007). The Classical Finance Theory (CFT) contends upon the rational investors' competition to optimize their portfolio's statistical properties with diversification to impact the prices. It ignores investors' sentiments (Baker & Wurgler 2006; Ding *et al*., 2018) and the irrational investor's offset demands while explaining the asset pricing models. Irrational investors trade against rational arbitrageurs to close the fundamental price setting process. According to Milgrom & Stokey (1982), such a type of trade underestimates asset prices sufficiency, and the irrational arbitrageurs disappear from the market.

Naik & Padhi (2016) opposed the opinion of CFT and explained that "noisy traders" are away from the necessary and in-depth information. Hence, they invest according to the noise signals, which are the root causes of deviation in assets' intuitive value and price movements. Therefore, sentiments toward noise cause fluctuation in market prices (Verma & Verma, 2007; Shahzad, Bouri, Roubaud, *et al*., 2020). Rational and irrational investors are both essential for a market like the two wheels of a vehicle. If all the investors are rational, perceiving the market fluctuations accurately, the individual assets trading level will be verve down (Milgrom & Stokey, 1982, Black, 1986; Salamat *et al*., 2020).

Kyle & Wang (1997) and Wang *et al*. (2007) elucidated the evolutionary process related dynamically to wealth accumulation growth. The irrational investor with under-confidence has fewer chances of survival. In contrast, optimism or little overconfidence makes the investor more dominant in investment in a relatively riskier environment. Baker and Wurgler (2006) mentioned investors' psychology in the financial market. They stated that if the sentiments are low in the beginning-of-period, the subsequent returns would be high for small, highly volatile non-dividend paying, non-profitable and distress stocks and *vice versa* when sentiments are high.

Bitcoin is the topmost currency of cryptocurrency, starting from the meagre price of $27 in 2009. In 2020, it has become the most capitalized contributor currency with a price of more than $10000 per Bitcoin. The risk of scams, economic bubbles, fraud, and cryptocurrency loss is ten times higher than in the stock market, creating a connection between investors' sentiments and Bitcoin volatility (Bouri *et al*., 2019, 2020a). The Bitcoin cryptocurrency is un-centralized, with no specific rules of entrance or exit. The technology-based investment and no particular reason for existence are strongly related to investors' pessimist and optimist behavior (Shahzad *et al*., 2019; Geng *et al*., 2021). If investors can gain faster by cryptocurrency, they can lose everything in the blink of an eye, as Mt. Gox lost Bitcoin worth $72 million in 2016. Vasek & Moore (2015) also elucidated 192 scam categories and 13000 victims in their research. Cryptocurrencies investment is more relevant to investor sentiment index than return index because of its uncertain and unpredictable characteristics. Investors' optimist behavior upsurges them to invest money in the riskiest cryptocurrency and *vice versa* (Bouri, Roubaud, & Shahzad, 2020). The short history of indexing has been oblivious due to the impact of investor sentiments on Bitcoin investment. Economic bubbles of cryptocurrency have a significant impact on investor sentiments.

1.1.1. Research Objectives

This study aimed:

- To study the sentiment index with a market data proxy approach regarding Bitcoin returns in the cryptocurrency market.
- To develop a sentiment index by using Principal Component Analysis.
- To check the relationship between the created sentiment index and Bitcoin returns.
- To check the created sentiment index by using market data proxies to either explain the Bitcoin market's behavior or not.

2. Study Background

Investors Sentiment and the Stock Market

Liu & An (2018) indicated that the investor sentiment asymmetrically has a significant effect on the CSI-300. Wang (2001) and Yang & Copeland (2014) examined the investor's sentiments that affect investors' future expectations. It is observed how investor sentiments, investors' irrational attitudes, and the market's high volatility are directly interlinked by using the multiple and individual market data proxies for the investors' sentiment. The market volatility and returns are influenced by investor sentiments' implications (Baker & Stein, 2004; Baker & Wurgler, 2006; Zhu, 2012; Chen *et al*., 2010; Yang & Hasuike, 2017). As mentioned above, a bulk of studies are focused on investors' sentiments and volatility of the stock market. Purposely, this research is to open new horizons of studying the effects of investor sentiments on the volatility of Bitcoin returns.

Investors Sentiment and Cryptocurrency with Bitcoin at the Forefront

Bitcoin is a cryptocurrency based on encrypted "blockchain" database technology (Li *et al*., 2021), which showed exposure in 2009. In 2011-2012, cryptocurrencies were unsettled. But the low conventional asset correlations induces portfolio investors' tremendous attention toward cryptocurrencies as a fashion (Bouri *et al*., 2017; Ji *et al*., 2018). Cryptocurrencies are not evaluated because practitioners' opinion is quite different due to the fraudulence and the future of currency (Bouri, Shahzad, & Roubaud, 2020a). Investor's sentiments are influenced by price fluctuation, social rumors, and other investors' actions. These determinants are quickly chased in this internet technological era via observation of significant cryptocurrency holders' trading action, known as "whales." The cryptocurrency market is highly dependent on socially constructed opinions. Menkhoff *et a*l. (2006) and Kristoufek (2015) explored that Bitcoin is more dependent on an idiosyncratic set of features as energy prices (Liu & An, 2018), the computer programming and cybercrime activities (Yelowitz & Wilson, 2015), the anonymity of users (Ober *et al*., 2013), and attractiveness as compared to the financial and economic market (Kristoufek, 2015; Shahzad, Bouri, Roubaud, et al., 2020).

Bitcoin is a riskier investment as compared to stock due to its decentralization, which considers investor sentiments a better explanation to price changes in hazardous investment. Bitcoin and investor sentiments are significantly related to each other regarding the explanation of Bitcoin return and volatility's fluctuation (Eom *et al*., 2019). As Eom *et al*., 2019 study shows, the past volatility does not help measure the future fluctuation by using the autoregressive model.

Sentiment Index and Bitcoin

The measurement of investors’ sentiment through accurate proxy indicators, which may explain sentiments more precisely, has become the vast area of investigation in behavioral finance. The observable and quantifiable proxies objectively and comprehensively reflect investors' opinions and guarantee investors’ sentiment results on the market. Usually, three types of investors’ sentiment proxies are observed in previous literature as single objective and single subjective sentiment indicators, which are the fundamental determinants of composite index creation. Single indicators indexing is used in divergent studies to measure the effect of investors’ sentiment regarding stock market volatility. Simultaneously, comprehensive sentiment indexes indicate mainstream sentiment index construction (He *et al.,* 2017). Previous literature enlightened the relationship between stock market volatility and investors’ sentiment (Stambaugh *et al.,* 2012; Ben-Rephael *et al.,* 2012; Chen *et al.,* 2010; Ning, 2009). The relationship of investors’ sentiment and specific industries' returns was measured (Huang *et al.,* 2014) using Principal Component Analysis (PCA). The nature of stock market volatility and Bitcoin cryptocurrency volatility is entirely different (Bouri, Shahzad, & Roubaud, 2020b; Shahzad, Bouri, Kayani, *et al*., 2020). This study urges new debate among the researchers to check the relationship between investor’s sentiment and Bitcoin return. The Market data proxy approach in which five investor sentiment proxies, *i.e.*, money flow index, Bitcoin index turnover, relative strength index, crypto index, and S & P global index, is used in the study because it quantifies the actual financial market beliefs of investors. By using Principal Component Analysis (PCA), the sentiment index is developed and then regressed with Bitcoin returns, unexplored in the existing literature.

3. Data and Research Methodology

This study comprises 208 values of the weekly Bitcoin data, taken from 1st January 2015 to 31st December 2018 during a highly volatile period for Bitcoin, which covers the complete trade cycle (See Figures 1 and 2).

Figure 1. Bitcoin Prices (2013-2018)

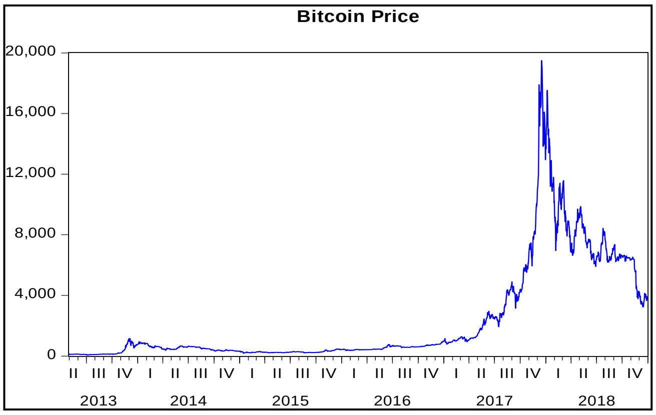
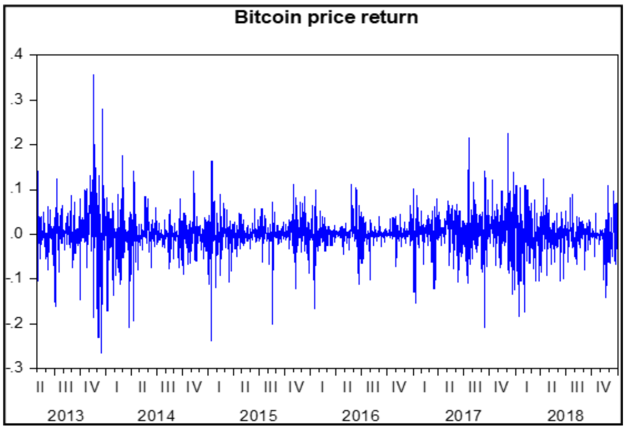


Figure 2. Bitcoin Price Return (2013-2018)



The weekly (Wednesday) data has been adopted in this study to avoid the white noise effect in the results and prevent the first and last day of the week and non-synchronized trade effect (Ng, 2000; Chiang and Doong, 2001; Bhar and Nikolova, 2009). Bitcoin research data has been extracted from the Coin Market Cap and World Coin Index, Cryptocurrency index-30 from CCI-30, and S&P index from Bloomberg Market.

Investors' sentiments represent the market participants' expectations based on market behavior, like bearish investors expecting a return below average and a bullish investor expecting an above-average return (Brown & Cliff, 2004). A bulk of the existing literature supports the market data proxy approach for measuring the stock market's investor sentiments because the market data proxy approach quantifies investors' actual behavior (pessimist or optimist). Baker & Wurgler (2007) developed a sentiment index by using six common proxies (trading volume based on turnover, dividend premium, the closed-end fund discount, the number and first-day returns on IPOs, and the equality share issue) for stock market investor sentiments. The study of Baker & Wurgler (2007) explored that the sentiment and speculative stock have an indirect proportionate relationship. The sentiment shows a diminishing trend, and speculative stocks have shown a rise in future returns, inconsistent with the classical asset pricing theories and *vice versa*. The researchers have used divergent proxies for investor sentiments as per the requirement of study purpose or availability of data. This research has adopted the methodology of Roy & Chan (2012) and Zia Ur Rehma*n et al*. (2017) with modification in variables pattern according to the cryptocurrency market.

The Investor Sentiments Index Model

The below model is designed to measure the sentiment index:

$$SMI_{BC,t} = \alpha_1 MFI + \alpha_2 BTURN + \alpha_3 RSI + \alpha_4 \Delta CI + \alpha_5 \Delta S\&P \quad Equation - 1$$

In equation -1 the standardized linear variables combination, $SMI_{BC,t}$ is a principal component which is representative of sentiment index, MFI is the representative of money flow index, $BTURN$ indicates Bitcoin index turnover, RSI is the relative strength index,

ΔCI is the variation of cryptocurrency index, and $\Delta S\&P$ is global index variations (Roy & Chan, 2012; Zia Ur Rehman *et al*., 2017).

Variables of the model are explained hereunder:

The Money Flow Index

The money flow index comprises weekly turnover information and ratio, calculation of weekly prices, and weekly money flow is necessary to measure the money flow index. Weekly prices and money flow is calculated by equations 2a and 2b.

$$weekly\ Prices = \frac{low+high+close}{3} \quad Equation - 2a$$

$$Money\ Flow = weekly\ Prices \times turnover \quad Equation - 2b$$

If the weekly prices are lower as compared to the last week, it is said to be negative money flow, and *vice versa*; the money flow index is determined by using the following equation-3 (Roy & Chan, 2012; Zia Ur Rehman *et al.*, 2017).

$$MFI = 100 \times \frac{Positive\ money\ flow_{week}}{Positive\ money\ flow_{week} + Negative\ money\ flow_{\ week}} \quad Equation - 3$$

The Bitcoin Turnover Ratio

A turnover ratio measures the Bitcoin index's trading activities, so the respective Bitcoin turnover ratio is included in the principal model. In the viewpoints of Ying (1966) and Zia Ur Rehman *et al*. (2017), the price rises by more considerable turnover (bullish market period) and price fall is associated with small turnover (bearish market period).

$$BTURN = 100 \times \frac{VM_{week}}{VM_{month}} \quad Equation - 4$$

In the above equation-4 VM_{week} is the average volume for a week and VM_{month} the average value for a month. $BTURN$ is calculated by adding one succeeding value and dropping one preceding value (Roy and Chan, 2012; Zia Ur Rehman *et al*., 2017).

The Relative Strength Index of Bitcoin Returns

The Bitcoin index's buying and selling activities are measured in the relative strength index's primary model. The following equation calculates the weekly RSI:

$$RSI_{week} = 100 \times \frac{\sum(P_t - P_{t-1})_+}{\sum|P_t - P_{t-1}|} \quad Equation - 5$$

where: $(P_t - P_{t-1})_+ = |P_t - P_{t-1}|\ if\ P_t - P_{t-1} > 0, otherwise = 0$

In equation-5 P_t is representative of current price and P_{t-1} shows the preceding price. RSI value higher than 80 indicates an overbought market, and RSI value less than 20 indicates an oversold market (Chen *et al*., 2010).

The Variation in Cryptocurrency Index (CI-30)

The Cryptocurrency index-30 variation measures Bitcoin investors' mood swing in the sentiments model (Liu and An, 2018). The variation of cryptocurrency index is calculated by the following equation-6:

$$\Delta CI = CI_t - CI_{t-1} \quad Equation - 6$$

The difference between the current price (CI_t) and preceding price (CI_{t-1}) of cryptocurrency index is the cryptocurrency index variation.

1.1.2. The Variation S&P Global BMI Index

The S&P Global BMI index publicly traded corporation of American is used as a proxy which deals with seven different currencies, and 11000 companies which are registered in it and fully float since initiation in 1989. The given equation-7 calculates the variation of S&P:

$$\Delta S\&P = S\&P_t - S\&P_{t-1} \; Equation - 7$$

ΔS&P shows the variation of the S&P global index concerning time, the time variation indicated by t (current price) and $t-1$ (previous price) as a subscript of S&P in equation-7.

1.1.3. Relationship of Sentiment Index and Bitcoin Returns

The sentiment index is regressed on the volatility of Bitcoin returns by following the methodology of Zia Ur Rehma*n et al*. (2017). The following equation is used to measure the Bitcoin returns $Y_{BC,t}$.

$$Y_{BC,t} = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \quad Equation - 8$$

In the above equation-8 $Y_{BC,t}$ is Bitcoin returns which are calculated by dividing P_t (current value) by P_{t-1} (one period before value), taking log and multiplication by 100. The below equation is used to check the relationship between Bitcoin returns and investor sentiments;

$$Y_{BC,t} = \alpha + Ln\beta SMI_{BC,t} \; Equation - 9$$

where: $Y_{BC,t}$ represents the Bitcoin return (dependent variable) and $SMI_{BC,t}$ is the sentiment index (independent variable). The α represents a constant, Ln the natural log, and β is the coefficient of SMI.

1.1.4. Principal Component Analysis

Principal Component Analysis (PCA) is used to an orthogonal transformation for observation conversion of a possibly correlated set of variables into a linearly uncorrelated set of variables values. The Principal Component Analysis purposely uses to reduce data dimensionality and identify new evocative principal variables (Chen *et al.,* 2014; Huang *et al.,* 2014; Yang & Hasuike, 2017). The investor sentiment's composite measure is developed by applying the principal component analysis to the variables mentioned above. The covariance matrix of eigenvalue and eigenvectors is obtained by standardization of variables. The first eigenvector related to the largest eigenvalue will construct the sentiment index as a linear combination of variables (Pearson, 1901; Huang *et al.,* 2014).

4. Results and discussions

Descriptive statistics of selected proxy variables for the sentiment index of Bitcoin prices are displayed in Table 1. The mean value of MFI (55.04204) and RSI (54.45488) is falling within the range of 10-90, which indicates a slight stability of Bitcoin price fluctuations. The falling region of MFI, RSI, and ΔCI's maximum and minimum values (above 70 and below 30) shows a trend of the unproductive market and oversold and overbought securities (Che*n et al*., 2014; Zia Ur Rehma*n et al*., 2017). The MFI and RSI of the Bitcoin prices indicate that the market somewhat behaves as the Bitcoin prices fluctuate. The mean value of S&P (0.051466) and BTURN (0.918744) is positive, while ΔCI (-1.63653) and RETURN (-0.0026) shown negative value as well as they do not lie within the range of 10-90, with 0.398406, 0.873441, 0.489416, and 0.000371 median values, respectively. The fluctuation range of S&P is from 4.736842 to -6.31068, BTURN from 2.077883 to 0.439755, ΔCI from 1029.155 to -1854.3, and RETURN from 0.181724 to -0.23757.

Table 1

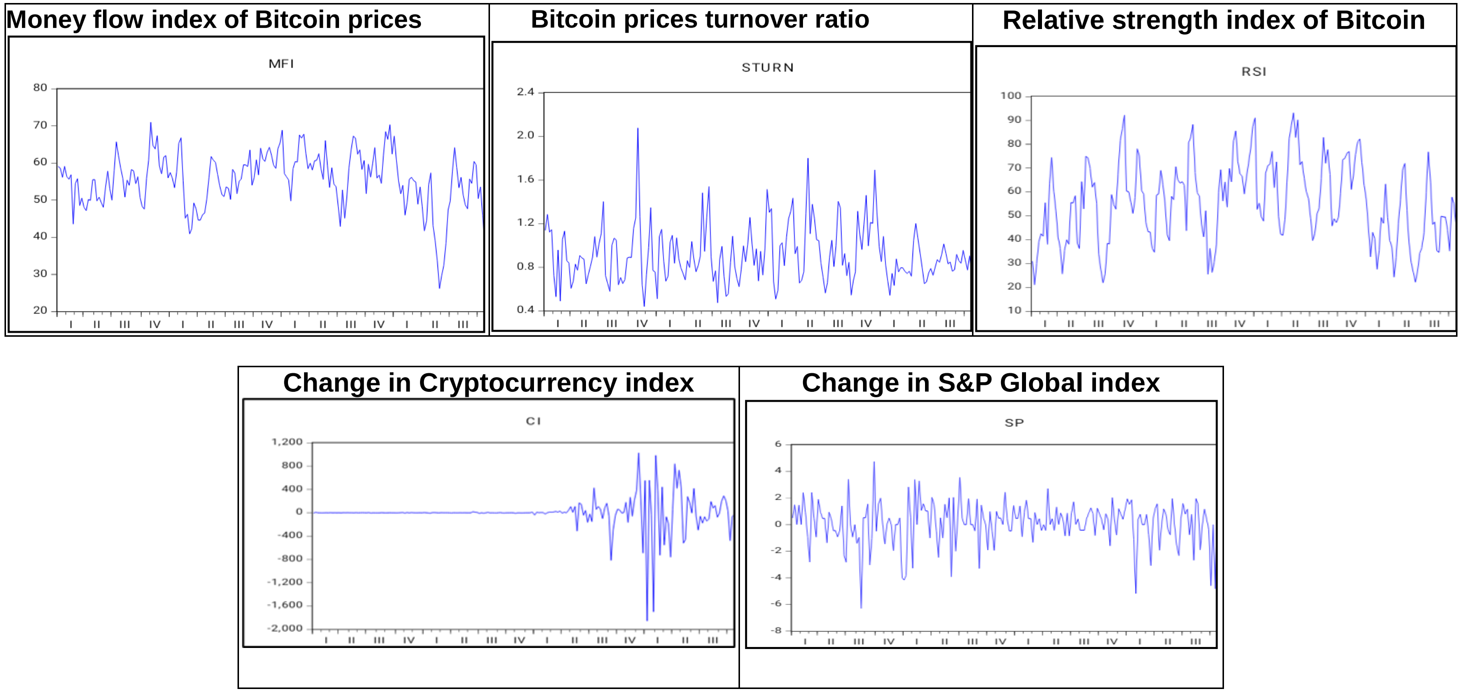
Descriptive statistics of the variables

	MFI	RSI	ΔSP	BTURN	ΔCI	RETURN
Mean	55.04204	54.45488	0.051466	0.918744	-1.63653	-0.0026
Median	55.84664	55.27319	0.398406	0.873441	0.489416	0.000371
Maximum	71.02404	93.17294	4.736842	2.077883	1029.155	0.181724
Minimum	26.19813	12.86825	-6.31068	0.439755	-1854.3	-0.23757
Std. Dev.	7.529947	17.62137	1.693177	0.253047	278.6251	0.043063
Skewness	-0.66919	0.010474	-0.784261	1.078874	-2.12455	-0.78339
Kurtosis	4.037203	2.338828	4.354166	5.081251	20.08983	9.261673
Jarque-Bera	24.84769	3.792426	37.21488	77.89155	2687.683	361.0824
Probability	0.000004	0.150136	0	0	0	0
Observations	208	208	208	208	208	208

The skewness values are positive and negative, as MFI, SP, CI, and RETURN are negative and RSI and BTURN are positive. The significance of Jarque-Bera at the 1% level rejects the null hypothesis of the normal distribution of values except for RSI. The Jarque-Bera value of RSI is insignificant and shows the normal distribution of values. This analysis consists of 208 values extracted from weekly observations for 4 years. The visual presentation of descriptive statistics for the money flow index, Bitcoin prices turnover, relative strength index, change in cryptocurrency index, and change in S & P global index is displayed in Figure 3.

Figure 3.

Descriptive statistics of variables



Principal Component Analysis of sentiment index variables

The Principal Component Analysis (PCA) of a specific set of variables is presented in Tables 2 and 3. PCA results have explained the first component of the primary model, which illustrates 38.68% of the total variance of the sample because it covers a significant part of the variables' common variation. The eigenvalue 1.934014 is also an enormous value and gets the support of the Kaiser Criterion factor retention method (Braeken & Van Assen, 2017), which is a relatively short but reliable scale of selection. The Principal Component Analysis (PCA) is used to generate an index of all study variables. (Finter *et al.,* 2012; Chong *et al.,* 2014) and graphically presented (see Figure 4) as follows.

$$SMI_{bc-t} = 0.549994MFI_{BC} + 0.554295BTURN_{BC} + 0.601331RSI_{BC} + 0.079334\Delta CI_{BC} + 0.149568\Delta SP_{BC}$$

Figure 4. The sentiment index

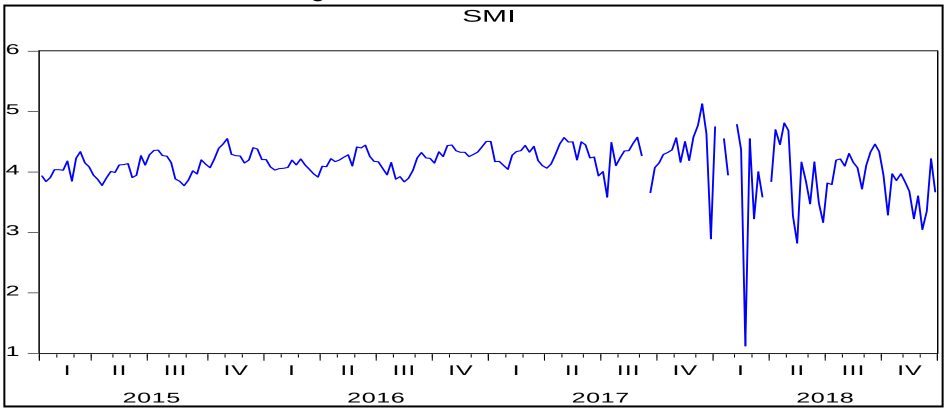


Table 2

PCA of the variables

The Eigenvalues						
Eigen values (sum=5, Average=1)	Number	Value	Difference	Proportion	Cumulative value	Cumulative proportion
	1	1.934014	0.83425	0.3868	1.934014	0.3868
	2	1.099764	0.196433	0.22	3.033779	0.6068
	3	0.903332	0.303262	0.1807	3.937111	0.7874
	4	0.60007	0.13725	0.12	4.53718	0.9074
	5	0.46282	---	0.0926	5	1

Table 3

The Eigenvector loadings

Variable	PC 1	PC 2	PC 3	PC 4	PC 5
MFI	0.549994	-0.17871	0.12026	0.690505	0.417504
RSI	0.601331	-0.08974	-0.00149	-0.02207	-0.79364
SP	0.149568	0.631431	0.751175	-0.11294	0.043659
BTURN	0.554295	-0.00293	-0.23374	-0.66717	0.43931
CI	0.079334	0.749196	-0.60551	0.254641	-0.03056

In Table 4, a correlation matrix is presented to check the multicollinearity among independent variables. The results indicated that no linear relationship was found by the multiple regression models among the independent variables. According to the multicollinearity rules, if the regressor value is higher than 0.80, then the data series encountered the severe problem of multicollinearity (Buyuksalvarci, 2010; Shafana, 2014; Ng, 2000). Our correlation matrix tended to be within the range of 0.494611 to -0.02903, which shows that the data series is free of multicollinearity by Pearson correlation analysis.

Table 4

Ordinary correlations

	MFI	RSI	SP	BTURN	CI
MFI	1				
RSI	0.494611	1			
SP	0.078239	0.096076	1		
BTURN	0.373228	0.492713	0.053787	1	
CI	-0.02903	0.026985	0.114464	0.102327	1

In Table 5, the results of regression show the coefficient (β), which is 0.015327 as a value of sentiment index, with a 0.0457 probability value. The sentiment index is significantly related to Bitcoin returns at a 5% level as per regression results (Baker & Wurgler, 2006; Chen *et al*., 2014). The coefficient significance value of SMI shows that investor sentiments strongly affect Bitcoin Prices volatility.

Table 5

The relationship between Bitcoin returns and sentiment index

	α (constant)	**β**
SMI (sentiment index)	-0.06577	**0.015327****
Prob.	(0.0385)	**(0.0457)**
T-statistic	[-2.08347]	**[2.010287]**

5. Discussion and conclusion

The results of research showed the impact of investor sentiments on Bitcoin cryptocurrency returns. Bitcoin was chosen for analysis due to two solid reasons. First, Bitcoin represents 2/3 of total cryptocurrencies, and Bitcoin was the first cryptocurrency with the maximum data available as compared to other cryptocurrencies. No doubt the current price and return fluctuation of Bitcoin is comparatively high as against other cryptocurrencies. It has also started from a very low price, which affects the investor sentiments for other currencies. The market data proxy approach has been used to generate a sentiment index with five variables, *i.e.*, MFI, BTURN, RSI, CI, and S&P. The sentiment index was regressed with Bitcoin returns, and the results positively support the relationship between them. This relationship indicates that a sentiment index concerning market data proxy played a relevant role in the cryptocurrency market. The future research possibilities will open up by this research in behavioral finance and digital finance.

Conclusion

This study has been conducted to grasp the behavioral finance concept of investors' sentiment and its impact on cryptocurrencies. We considered the Bitcoin currency and constructed an index by using the Principal Component Analysis (PCA) for market data proxies for sentiments, *i.e.*, Money Flow Index (MFI), Bitcoin Index Turnover (BTURN), Relative Strength Index (RSI), Variation in Cryptocurrency Index (ΔCI) and changes in Global Index ($\Delta S\&P$). The selected variables showed no correlation with each other since the lag-1 of the eigenvalues is higher. We selected the first Principal Component (PC-1) to construct the sentiment index based on the eigenvalue. This index was then regressed upon the returns of the Bitcoin currency. Results showed that the Investor's sentiments significantly influenced Bitcoin returns; thus, the constructed investor sentiments index came out as a good indicator of Bitcoin currency's return pattern. This research would contribute substantially to future research work, examining the effect of investor's sentiments on Bitcoin volatility and investment predictability with the consistent property, which is influenced by the sentiments and spreading rumors. This study is essential for the researchers, investors, and economists to check Bitcoin returns' fluctuation due to the investor's psychology or sentiments. It will open up a new debate on Bitcoin's un-explored side that optimist investors take the risk of investing their money in highly volatile and risky technology-based investments. The pessimist investors may shun the investment in cryptocurrency due to previous mishaps or scam cases.

Limitation and future study direction

In this research, only Bitcoin was chosen for investor sentiment analysis due to limited data availability and resources. Cryptocurrency is expanding day by day, and new currencies are added to the existing collection. Researchers can conduct research with considerable data period and top 30 cryptocurrencies as well as different digital currencies. Other measuring methods or proxies like Potential Sentiment Proxies and Orthogonalising Sentiment Index with different control or behavioral variables might be used in future research.

References

Baker, M. and Stein, J.C., 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets*, 7(3), pp.271-299.

Baker, M. and Stein, J.C., 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets*, 7(3), pp.271-299. https://doi.org/10.1016/j.finmar.2003.11.005

Baker, M. and Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4), pp.1645-1680.

Baker, M. and Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4), pp.1645-1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x.

Baker, M. and Wurgler, J., 2007. Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2), pp.129-152.

Baker, M. and Wurgler, J., 2007. Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2), pp.129-152. https://doi.org/10.1257/jep.21.2.129.

Ben-Rephael, A., Kandel, S. and Wohl, A., 2012. Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics,* 104(2), pp.363-382.

Ben-Rephael, A., Kandel, S. and Wohl, A., 2012. Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics,* 104(2), pp.363-382. https://doi.org/10.1016/j.jfineco.2010.08.018.

Bhar, R. and Nikolova, B., 2009. Return, volatility spillovers and dynamic correlation in the BRIC equity markets: An analysis using a bivariate EGARCH framework. *Global Finance Journal,* 19(3), pp.203-218.

Bhar, R. and Nikolova, B., 2009. Return, volatility spillovers and dynamic correlation in the BRIC equity markets: An analysis using a bivariate EGARCH framework. *Global Finance Journal,* 19(3), pp.203-218. https://doi.org/10.1016/j.gfj.2008.09.005.

Black, F., 1986. Noise. *The Journal of Finance*, 41(3), pp.528-543. https://doi.org/10.1111/j.1540-6261.1986.tb04513.x.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D. and Hagfors, L.I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters,* 20, pp.192-198. https://doi.org/10.1016/j.frl.2016.09.025.

Bouri, E., Roubaud, D. and Shahzad, S.J.H., 2020. Do Bitcoin and other cryptocurrencies jump together? *The Quarterly Review of Economics and Finance*, 76, pp.396-409. https://doi.org/10.1016/j.qref.2019.09.003.

Bouri, E., Shahzad, S.J.H. and Roubaud, D., 2019. Co-explosivity in the cryptocurrency market. *Finance Research Letters*, 29, pp.178-183. https://doi.org/10.1016/j.frl.2018.07.005.

Bouri, E., Shahzad, S.J.H. and Roubaud, D., 2020a. Cryptocurrencies as hedges and safe-havens for US equity sectors. *The Quarterly Review of Economics and Finance*, 75, pp.294-307. https://doi.org/10.1016/j.qref.2019.05.001.

Bouri, E., Shahzad, S.J.H. and Roubaud, D., 2020b. Cryptocurrencies as hedges and safe-havens for US equity sectors. *The Quarterly Review of Economics and Finance*, 75, pp.294-307. https://doi.org/10.1016/j.qref.2019.05.001.

Bouri, E., Shahzad, S.J.H., Roubaud, D., Kristoufek, L. and Lucey, B., 2020. Bitcoin, gold, and commodities as safe havens for stocks: new insight through wavelet analysis. *The Quarterly Review of Economics and Finance*, 77, pp.156-164. https://doi.org/10.1016/j.qref.2020.03.004.

Braeken, J. and Van Assen, M.A., 2017. An empirical Kaiser criterion. *Psychological Methods*, 22(3), p.450. https://doi.org/10.1037/met0000074.

Brown, G.W. and Cliff, M.T., 2004. Investor sentiment and the near-term stock market. *Journal of Empirical Finance,* 11(1), pp.1-27. https://doi.org/10.1016/j.jempfin.2002.12.001.

Buyuksalvarci, A., 2010. The effects of macroeconomics variables on stock returns: Evidence from Turkey. *European Journal of Social Sciences*, 14(3), pp.404-416.

Chen, H., Chong, T.T.L. and Duan, X., 2010. A principal-component approach to measuring investor sentiment. *Quantitative Finance,* 10(4), pp.339-347. https://doi.org/10.1080/14697680903193389.

Chen, H., Chong, T.T.L. and She, Y., 2014. A principal component approach to measuring investor sentiment in China. *Quantitative Finance*, 14(4), pp.573-579. https://doi.org/10.1080/14697688.2013.869698.

Chiang, T.C. and Doong, S.C., 2001. Empirical analysis of stock returns and volatility: Evidence from seven Asian stock markets based on TAR-GARCH model. *Review of Quantitative Finance and Accounting*, 17(3), pp.301-318. https://doi.org/10.1023/A:1012296727217.

Chong, T.T.L., Cao, B. and Wong, W.K., 2014. A new principal-component approach to measure the investor sentiment. http://dx.doi.org/10.2139/ssrn.2631910.

Ding, W., Mazouz, K. and Wang, Q., 2019. Investor sentiment and the cross-section of stock returns: new theory and evidence. *Review of Quantitative Finance and Accounting*, 53(2), pp.493-525. https://doi.org/10.1007/s11156-018-0756-z.

Eom, C., Kaizoji, T., Kang, S.H. and Pichl, L., 2019. Bitcoin and investor sentiment: statistical characteristics and predictability. *Physica A: Statistical Mechanics and its Applications,* 514, pp.511-521. https://doi.org/10.1016/j.physa.2018.09.063.

Finter, P., Niessen-Ruenzi, A. and Ruenzi, S., 2012. The impact of investor sentiment on the German stock market. *Zeitschrift für Betriebswirtschaft*, 82(2), pp.133-163. https://doi.org/10.1007/s11573-011-0536-x.

Geng, J.B., Du, Y.J., Ji, Q. and Zhang, D., 2021. Modeling return and volatility spillover networks of global new energy companies. *Renewable and Sustainable Energy Reviews*, 135, p.110214. https://doi.org/10.1016/j.rser.2020.110214.

He, G., Zhu, S. and Gu, H., 2017. A PLS Approach to Measuring Investor Sentiment in Chinese Stock Market. *Discrete Dynamics in Nature and Society*, 2017. https://doi.org/10.1155/2017/2387543.

Huang, C., Yang, X., Yang, X. and Sheng, H., 2014. An empirical study of the effect of investor sentiment on returns of different industries. *Mathematical Problems in Engineering*, 2014. https://doi.org/10.1155/2014/545723.

Ji, Q., Bouri, E., Gupta, R. and Roubaud, D., 2018. Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. *The Quarterly Review of Economics and Finance*, 70, pp. 203-213. https://doi.org/10.1016/j.qref.2018.05.016.

Kristoufek, L., 2015. What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS one*, 10(4), p.e0123923. https://doi.org/10.1371/journal.pone.0123923.

Kyle, A.S. and Wang, F.A., 1997. Speculation duopoly with agreement to disagree: Can overconfidence survive the market test? *The Journal of Finance*, 52(5), pp.2073-2090. https://doi.org/10.1111/j.1540-6261.1997.tb02751.x.

Li, X., Zhang, D., Zhang, T., Ji, Q. and Lucey, B., 2021. Awareness, energy consumption and pro-environmental choices of Chinese households. *Journal of Cleaner Production*, 279, p.123734. https://doi.org/10.1016/j.jclepro.2020.123734.

Liu, C. and An, Y., 2018. Investor sentiment and the basis of csi 300 stock index futures: An empirical study based on qvar model and quantile regression. *Discrete Dynamics in Nature and Society,* 2018. https://doi.org/10.1155/2018/4783214.

Menkhoff, L., Schmidt, U. and Brozynski, T., 2006. The impact of experience on risk taking, overconfidence, and herding of fund managers: Complementary survey evidence. *European Economic Review*, 50(7), pp. 1753-1766. https://doi.org/10.1016/j.euroecorev.2005.08.001.

Milgrom, P. and Stokey, N., 1982. Information, trade and common knowledge. J*ournal of Economic Theory*, 26(1), pp.17-27. https://doi.org/10.1016/0022-0531(82)90046-1.

Mohsin, M., Naiwen, L., Zia-UR-Rehman, M., Naseem, S. and Baig, S.A., 2020. The volatility of bank stock prices and macroeconomic fundamentals in the Pakistani context: an application of GARCH and EGARCH models. *Oeconomia Copernicana,* 11(4), pp.609-636. https://doi.org/10.24136/oc.2020.025.

Mohsin, M., Naseem, S., Zia-ur-Rehman, M., Baig, S.A. and Salamat, S., The crypto-trade volume, GDP, energy use, and environmental degradation sustainability: An analysis of the top 20 crypto-trader countries. *International Journal of Finance & Economics*. https://doi.org/abs/10.1002/ijfe.2442.

Naik, P.K. and Padhi, P., 2016. Investor sentiment, stock market returns and volatility: evidence from National Stock Exchange of India. *International Journal of Management Practice*, 9(3), pp.213-237. https://doi.org/10.1504/IJMP.2016.077816.

Ng, A., 2000. Volatility spillover effects from Japan and the US to the Pacific–Basin. *Journal of International Money and Finance,* 19(2), pp.207-233. https://doi.org/10.1016/S0261-5606(00)00006-1.

Ning, Y.Z.M., 2009. Research on the Measurement of Investor Sentiment in Chinese Stock Market: the CICSI's Construction [J]. J*ournal of Financial Research*, 11, p.014. http://en.cnki.com.cn/Article_en/CJFDTotal-JRYJ200911014.htm.

Ober, M., Katzenbeisser, S. and Hamacher, K., 2013. Structure and anonymity of the bitcoin transaction graph. *Future Internet*, 5(2), pp.237-250. https://doi.org/10.3390/fi5020237.

Pearson, K., 1901. LIII. On lines and planes of closest fit to systems of points in space. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 2(11), pp.559-572. https://doi.org/10.1080/14786440109462720.

Rehman, M.Z.U., ul Abidin, Z., Rizwan, F., Abbas, Z. and Baig, S.A., 2017. How investor sentiments spillover from developed countries to developing countries? *Cogent Economics & Finance*, 5(1), p.1309096. https://doi.org/10.1080/23322039.2017.1309096.

Roy, R. and Chan, N.W., 2012. An assessment of agricultural sustainability indicators in Bangladesh: review and synthesis. *The Environmentalist*, 32(1), pp.99-110. https://doi.org/10.1007/s10669-011-9364-3.

Salamat, S., Lixia, N., Naseem, S., Mohsin, M., Zia-ur-Rehman, M., & Baig, SA 2020. Modeling Cryptocurrencies Volatility Using Garch Models: A Comparison Based on Normal and Student's T-Error Distribution. *Entrepreneurship and Sustainability Issues*, 7(3), pp.1580-1596. https://ssrn.com/abstract=3585406.

Shafana, M.A.C.N., 2014. Macroeconomic variables effect on financial sector performance in Emerging Sri Lankan Stock Market. *International Journal of Science and Research,* 3(10), pp. 227-231. https://pdfs.semanticscholar.org/e19d/1ce5b0175f71cf00fe788f706bf8d3b2f12a.pdf.

Shahzad, S.J.H., Bouri, E., Kayani, G.M., Nasir, R.M. and Kristoufek, L., 2020. Are clean energy stocks efficient? Asymmetric multifractal scaling behaviour. *Physica A: Statistical Mechanics and its Applications,* 550, p.124519. https://doi.org/10.1016/j.physa.2020.124519.

Shahzad, S.J.H., Bouri, E., Roubaud, D. and Kristoufek, L., 2020. Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin. *Economic Modelling*, 87, pp.212-224. https://doi.org/10.1016/j.econmod.2019.07.023.

Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L. and Lucey, B., 2019. Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis*, 63, pp.322-330. https://doi.org/10.1016/j.irfa.2019.01.002.

Stambaugh, R.F., Yu, J. and Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics,* 104(2), pp.288-302. https://doi.org/10.1016/j.jfineco.2011.12.001.

Vasek, M. and Moore, T., 2015, January. There's no free lunch, even using Bitcoin: Tracking the popularity and profits of virtual currency scams. In International conference on financial cryptography and data security (pp. 44-61). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-47854-7_4.

Verma, R. and Verma, P., 2007. Noise trading and stock market volatility. *Journal of Multinational Financial Management,* 17(3), pp. 231-243. https://doi.org/10.1016/j.mulfin.2006.10.003.

Wang, F.A., 2001. Overconfidence, investor sentiment, and evolution. *Journal of Financial Intermediation,* 10(2), pp.138-170. https://doi.org/10.1006/jfin.2001.0311.

Wang, L., Chu, J. and Wu, J., 2007. Selection of optimum maintenance strategies based on a fuzzy analytic hierarchy process. *International journal of production economics*, 107(1), pp.151-163. https://doi.org/10.1016/j.ijpe.2006.08.005.

Yang, Y. and Copeland, L., 2014. The effects of sentiment on market return and volatility and the cross-sectional risk premium of sentiment-affected volatility (No. E2014/12). *Cardiff economics working papers*. https://www.econstor.eu/handle/10419/109058.

Yang, Y. and Hasuike, T., 2017, July. Construction of Investor Sentiment Index in the Chinese Stock Market. In 2017 6th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI) (pp. 23-28). IEEE. https://doi.org/10.1109/IIAI-AAI.2017.93.

Yelowitz, A. and Wilson, M., 2015. Characteristics of Bitcoin users: an analysis of Google search data. *Applied Economics Letters*, 22(13), pp.1030-1036. https://doi.org/10.1080/13504851.2014.995359.

Ying, C.C., 1966. Stock market prices and volumes of sales. *Econometrica: Journal of the Econometric Society*, pp. 676-685. https://doi.org/10.2307/1909776.

Zhu, X., 2012. Investor sentiment and volatility of stock index an empirical analysis from the perspective of behavioral finance. *Advances in Applied Economics and Finance*, 3(4), pp.627-629.