The relationship between changes in investor sentiment and cryptocurrency prices

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Abstract

This research provides empirical evidence on whether investor sentiment plays a role in the cryptocurrency asset-pricing dynamics. My models include OLS regression and binary correlation analysis. I find: (1) the volatilities of sentiment changes and returns have a significant correlation, (2) sentiment changes and returns in the same period are significantly correlated at both weekly and daily frequencies, (3) sentiment has a statistically significant forecasting power on the next day's volatility, and (4) future sentiment is influenced positively by past returns and negatively by past sentiment.

Keywords: cryptocurrency trading, investor sentiment, return forecasting, volatility forecasting

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1. Introduction

A cryptocurrency (or crypto currency) is a digital asset designed to work as a medium of exchange that uses cryptography to secure its transactions, control the creation of additional cryptocurrencies, and verify the secure transfer of assets. Cryptocurrencies can be classified as types of digital or alternative currencies, distinct from traditional currencies in that they are founded on the principle of decentralized control, compared to the central banking systems that typical currencies rely on. The inception of cryptocurrencies dates back to 2008, when an unknown entity under the pseudonym Satoshi Nakamoto publically released a paper titled Bitcoin: A Peer-toPeer Electronic Cash System. In January 2009, Nakamoto implemented the bitcoin software as open source code, releasing it to the public on SourceForge. Nakamoto's contributions galvanized a wave of public attention, spurring others to create alternative cryptocurrencies that relied on the same fundamental technology but were specialized in purpose.

This wave of new cryptocurrencies has received much attention by the media and investors alike due to the assets' innovative features, potential capability as transactional tools, and tremendous price fluctuations. In the past few years, the total value of the entire cryptocurrency market has grown exponentially, and it is the result of both increased investor speculation and the introduction of various new cryptocurrencies, with current estimates of the total number of cryptocurrencies topping 1, 400 different coins. Thus, analyzing evolutionary dynamics of the cryptocurrency market is a topic of current interest and can provide useful insight about the market share of cryptocurrencies. Moreover, longitudinal datasets of Bitcoin transactions have been used to identify the socioeconomic drivers in cryptocurrency adoption.

The speculation behind these digital assets has increased to such magnitudes that even cryptocurrencies with no functionality have surpassed the market value of established companies whose stocks are publicly traded in the equity markets. This rapid and exponential increase in cryptocurrency prices suggests that price fluctuations are driven primarily by retail investor speculation, and that this market exhibiting signs of a financial bubble. Noteworthy, there has been increasing attention paid to improving our understanding of cryptocurrency market behavior.

Given that the alternative cryptocurrency market is dominated by retail investors, with few large institutional investors, sentiment on social media platforms and online forums may present a viable medium to capture total investor sentiment. More recently, it has been shown that social media data such as Twitter can be used to track investor sentiment, and price changes in the Bitcoin market and other predominant cryptocurrencies. In Ref., the authors demonstrate that Twitter sentiment, alongside economic signals of volume, price of exchange for USD, adoption of the Bitcoin technology, overall trading volume could be used to predict price fluctuations.

Market sentiment is a combination of all the views, thoughts and opinions of all the participants from the whole market. Most markets think the best explanation for the current direction of the market is dominant sentiment or ideas. So this article examines the relationship between investor sentiment and cryptocurrency prices. Although we can't tell the market what we think it should do, we can do is react to what's happening in the market.

2. Data and methodology

2.1. Data source

The sentiment data I used is Fear & Greed Index on *https://alternative.me*, which was derived from different emotional sources, like Twitter, Reddit. As is shown, a value of 0 means "Extreme Fear" while a value of 100 represents "Extreme Greed". Besides, I took advantage of close for 2018-2019 on BTC.USDT (Binance) as the follow figure.

2.2. Binary correlation analysis

I analyzed the correlation of volatility between sentiment changes and returns, and the correlation of contemporaneous sentiment changes and return.

2.3. OLS regression

I investigated the relationship between daily annualized volatility and sentiment changes using the following regression model.

$$VOL_t = \alpha + \beta_1 VOL_{t-1} + \beta_2 S_{t-1} + a_0 \tag{1}$$

I also investigated daily emotional prediction of past emotions and returns using the following regression model.

$$S_t = \alpha + \beta_1 R_{t-1} + \beta_2 S_{t-1} + \alpha_0 \tag{2}$$

3. Empirical analysis

Figure 1 reports that sentiment changes show a certain similarity to the trend of the change in the daily and weekly close, especially when close fluctuates greatly, sentiment change also shows the same trend, which is more obvious at the weekly frequency.

Table 1 shows that correlation between volatility of sentiment changes and returns is significant only on weekly basis. There was a significant correlation at the 0.01 level (bilateral).

Table 2 shows that sentiment changes and returns in the same period are significantly correlated in weekly and daily degrees, and the significant correlation both at the 0.01 level (bilateral).

Table 3 reports that sentiment does have a statistically significant forecasting power onto next day's volatility. This multiple regression set up controls the past day's volatility, and sentiment does have a statistically significant forecasting power onto next day's volatility.

Table 4 reports that future sentiment is influenced positively by past returns and negatively by past sentiment. The positive coefficient on past return reflects the intuition that if past returns are high, traders tend to have higher (more bullish) sentiment, whereas the negative coefficient on past sentiment reflects the mean-reverting nature of the sentiment series.

4. Conclusion

In conclusion, there are multiple links between investor sentiment and cryptocurrency prices. As such, given the complete lack of research within this academic sphere, my model serves as a proof of concept that social media platforms such as twitter can be used to capture investor sentiment, and that this sentiment is an early signal to future price fluctuations in cryptocurrencies.

Lastly, it would be interesting to further train and test my model over a longer time period. My results suggest a necessity to devote further resources and investments that would enable me to implement study how to use these connections to develop a cryptocurrency price prediction model.

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Appendix

Appendix A: variable definitions

Variables	Definition & Description
Sentiment changes	Describe the changes in sentiment during the day. It is calculated by subtracting the day's sentiment from the day after.
Close	The closing prices.
Return	Describe the changes in Return during the day. Using the closing price of the day and the day after
St	Describe the changes in sentiment during the day after t. It is calculated by subtracting the day's sentiment from the day after.. Embodying the connection with the future
St-1	Describe the changes in sentiment during the day. It is calculated by subtracting the day's sentiment from the day after.
Rt-1	Describe the changes in Return during the day.
S_V	Volatility of sentiment changes.
R_V	Volatility of cryptocurrency returns.

Figure 1
Daily and weekly sentiment changes and closing trend comparison

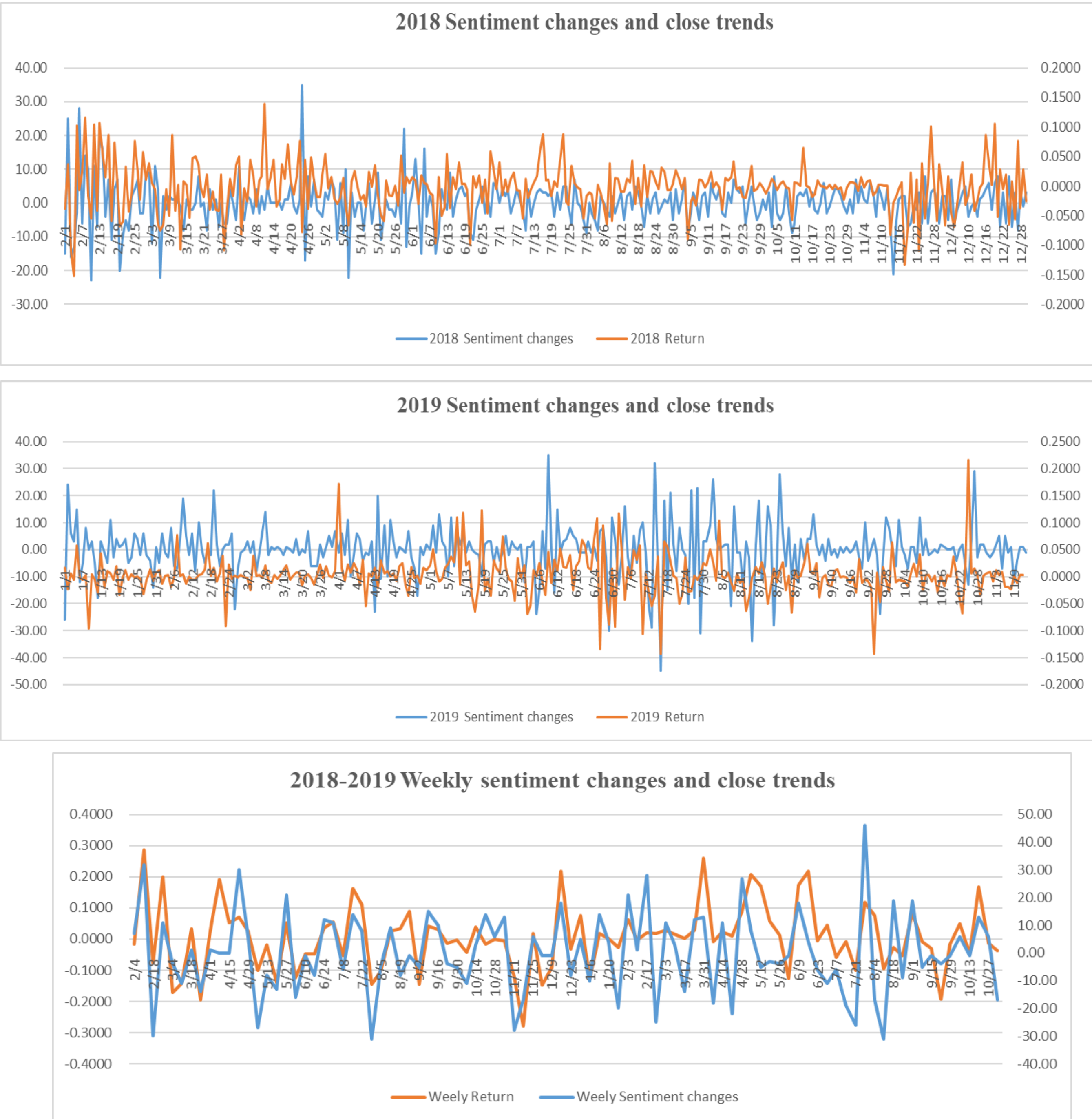

Table 1
The correlation of volatility between sentiment changes and returns

The results of these two tables show that the correlation between their volatility is significant only on a weekly basis.

Daily				Sv	Rv
Volatility of sentiment changes	Pearson correlation			1	-.076
	Significance (bilateral)				.053
	N			646	646
	Bootstrapa	Deviation		0	.002
		Standard error		0	.050
		95% confidence interval	Bottom line	1	-.171
			Top line	1	.019
Volatility of returns	Pearson correlation			-.076	1
	Significance (bilateral)			.053	
	N			646	646
	Bootstrapa	Deviation		.002	0
		Standard error		.050	0
		95% confidence interval	Bottom line	-.171	1
			Top line	.019	1

Weekly				Sv	Rv
Volatility of sentiment changes	Pearson correlation			1	0.629**
	Significance (bilateral)				0
	N			89	89
	Bootstrapa	Deviation		0	0.002
		Standard error		0	0.052
		95% confidence interval	Bottom line	1	0.529
			Top line	1	0.729
Volatility of returns	Pearson correlation			0.629**	1
	Significance (bilateral)			0	
	N			89	89
	Bootstrapa	Deviation		0.002	0
		Standard error		0.052	0
		95% confidence interval	Bottom line	0.529	1
			Top line	0.729	1
**There was a significant correlation at the.01 level (bilateral).					

Table 2
Contemporaneous bivariate correlation analysis

The results show that sentiment changes and returns in the same period are significantly correlated in both weekly and daily degrees.

Daily				Sentiment changes	Return
Sentiment changes	Pearson correlation			1	.102**
	Significance (bilateral)				0.01
	N			645	645
	Bootstrapa	Deviation		0	0.002
		Standard error		0	0.044
		95% confidence interval	Bottom line	1	0.015
			Top line	1	0.19
Return	Pearson correlation			.102**	1
	Significance (bilateral)			0.01	
	N			645	645
	Bootstrap[a]	Deviation		0.002	0
		Standard error		0.044	0
		95% confidence interval	Bottom line	0.015	1
			Top line	0.19	1
**. There was a significant correlation at the.01 level (bilateral).					
Weekly				Sentiment changes	Return
Sentiment changes	Pearson correlation			1	.593**
	Significance (bilateral)				0
	N			90	90
	Bootstrap[a]	Deviation		0	0
		Standard error		0	0.049
		95% confidence interval	Bottom line	1	0.492
			Top line	1	0.682
Return	Pearson correlation			.593**	1
	Significance (bilateral)			0	
	N			90	90
	Bootstrap[a]	Deviation		0	0
		Standard error		0.049	0
		95% confidence interval	Bottom line	0.492	1
			Top line	0.682	1
**. There was a significant correlation at the.01 level (bilateral).					

Table 3

Prediction of Daily Annualized Volatility and sentiment changes on Daily Annualized

I investigate the relationship between Daily Annualized Volatility and sentiment changes using the following regression model.

$$VOLt = \alpha + \beta 1VOLt\text{-}1 + \beta 2St\text{-}1 + ei$$

Sentiment does have a statistically significant forecasting power onto next day's volatility, as the t-stat in the following table of yours is greater than 1.98.

Coefficient						
		Unstandardized coefficient		Beta	t	Sig.
		B	Standard error			
Equation	(constant)	.111	.029		3.842	.000
	The previous days' sentiment index（St-1）	.001	.001	.051	2.104	.036
	The previous days' Annualized Volatility（VOLt-1）	.770	.024	.783	32.030	.000

Table 4

Daily emotional prediction of past emotions and returns

I investigate daily emotional prediction of past emotions and returns using the following regression model.

$$St = \alpha + \beta 1Rt\text{-}1 + \beta 2St\text{-}1 + ei$$

It seems future sentiment is influenced positively by past returns and negatively by past sentiment. The positive coefficient on past return reflects the intuition that if past returns are high, traders tend to have higher (more bullish) sentiment, whereas the negative coefficient on past sentiment reflects the mean-reverting nature of the sentiment series.

Coefficient						
		Unstandardized coefficient				
		B	Standard error	Beta	t	Sig.
Equation	（constant）	.033	.293		.112	.911
	Rt-1	79.841	7.520	.379	10.617	.000
	St-1	-.260	.036	-.260	-7.290	.000