Sentiment in the Cross Section of Cryptocurrency Returns

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Abstract

In this paper, we analyze sentiment in the cross-section of cryptocurrency returns. We construct a cryptocurrency sentiment index named "CryptoSent." Our findings indicate that cryptocurrencies with high absolute sensitivities to CryptoSent innovations tend to yield lower average returns in the following month and week. We introduce a sentiment factor as a common risk factor in the cross-sectional returns of cryptocurrencies, alongside market, size, and momentum factors. By incorporating the sentiment factor, the four-factor model explains an additional 13% of the weekly expected cryptocurrency returns. The sentiment factor possesses both economic and statistical significance when explaining eleven cryptocurrency characteristics-based long-short strategies.

Keywords: Cryptocurrency, Sentiment, Factor Model, Cross Section, Return Prediction.

JEL Classification: G12, G40

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1 Introduction

Cryptocurrency, a form of digital or virtual currency, relies on cryptography—an approach that utilizes mathematical algorithms for securing and verifying transactions. Diverging from conventional currencies, which are typically issued and backed by governments or central authorities, cryptocurrencies operate in a decentralized manner, free from any central control. With the introduction of Bitcoin by Nakamoto (2008), the cryptocurrency market has risen to prominence as a significant asset class within the financial sector. At the outset of 2021, the global cryptocurrency market cap had exceeded $1 trillion[1], and it is projected to continue its rapid growth at an estimated rate of 12.5% annually[2]. As noted by Shiller (2014), asset prices are often influenced by investor emotions and can be amplified by news and media coverage. Cryptocurrency, being an emerging asset class, is especially vulnerable to the sway of investor sentiment.

The study of sentiment and its impact on the cryptocurrency market has attracted significant attention and extensive research in recent years. Various studies have revealed that news articles and social media posts can exert a substantial influence on sentiment within cryptocurrency markets[3]. Makarov and Schoar (2021), Canayaz, Cao, Nguyen, and Wang (2023), Philippas, Rjiba, Guesmi, and Goutte (2019), as well as Liu and Tsyvinski (2021), among others, have documented that Bitcoin trading is heavily influenced by investor sentiment. Considering these findings, it's paramount for investors to factor in sentiment when making decisions about cryptocurrencies. However, it's crucial to emphasize that more research is needed to further unravel the intricate relationship between sentiment and cryptocurrency market returns.

[1] https://www.coingecko.com/en/global-charts#:~:text=The%20global%20cryptocurrency%20market%20cap,a%20Bitcoin%20dominance%20of%2047.39%25

[2] https://www.grandviewresearch.com/industry-analysis/cryptocurrency-market-report#:~:text=The%20global%20cryptocurrency%20market%20is,USD%2011.71%20billion%20by%202030

[3] Several papers have delved into the connection between sentiment and adoption, consistently revealing that positive sentiment can foster increased adoption, and vice versa. For instance, Choi et al. (2020) discovered that positive sentiment towards Bitcoin was closely linked to higher levels of adoption in Korea. Likewise, Kliber et al. (2018) observed that positive sentiment surrounding cryptocurrencies correlated with elevated trading volumes.

Cryptocurrencies are not only utilized as mediums of exchange for goods and services, but they are also frequently traded for speculative purposes, mirroring commodities such as gold. Among the most recognized names in this domain are Bitcoin, Ethereum, Litecoin, Ripple, and Dogecoin. Nevertheless, the market is vast, with thousands of unique cryptocurrencies, each with its own set of features and attributes. In this paper, we conduct on a detailed examination of over 2,000 cryptocurrencies over a considerable span from January 2014 to February 2023. Our daily dataset, comprising market snapshots, is sourced from CoinMarketCap, a leading cryptocurrency vendor. This data provides various metrics, including price, total supply, 24-hour trading volume, and descriptive keywords related to each cryptocurrency, among other aspects.

This paper makes its contribution in three important ways. First, we construct a cryptocurrency sentiment index called CryptoSent, capturing essential dynamics of sentiment's influence on cryptocurrency markets. Canayaz, Cao, Nguyen, and Wang (2023) use social media sentiment to predict the cryptocurrency returns. Han, Liu, and Sui (2023) find the contagion of bitcoin social media sentiment among investors. Chen, Guo, and Renault (2019) observe that cryptocurrency social media sentiment leads to market bubbles. In stock markets, Baker, and Wurgler (2006) form the top-down stock market sentiment index based on the macroeconomic conditions. We follow their work and construct CryptoSent using combinations of crypto markets performance, social media attention and blockchain activities, which contains cryptocurrency market index, market volatility, market volume, google trends, tweets discussion and number of active wallets on blockchain as the proxy of the top-down cryptocurrency markets sentiment index.

Secondly, we study CryptoSent's predictive capabilities within the cross-section of cryptocurrency returns. Ang, Hodrick, Xing, and Zhang (2006) show that stocks with high sensitivities to innovations in aggregate volatility have low average returns. We follow their methodology to sort cryptocurrencies by their respective sensitivity to CryptoSent. Our findings indicate that cryptocurrencies demonstrating high sensitivities to changes in CryptoSent are inclined to produce lower average returns in the following month and subsequent week. Frazzini, and Lamont (2008) find retailed investors are buying sentiment-related stocks and losing “dumb money,” our result which states holding sentiment-sensitive cryptocurrencies causing money loss is consistent with theirs. Our results indicate that sentiment is a risk factor in the cryptocurrency market, having a negative bearing on expected cryptocurrency returns regardless of their directional signs. Interestingly, cryptocurrencies relatively impervious to sentiment outpace their sentiment-susceptible counterparts a significant weekly advantage of 1.7%[4].

Finally, yet importantly, we introduce the sentiment factor as a common risk factor in cross-sectional cryptocurrency returns. Kumar, and Lee (2006) find that retailed sentiment is concentrated in hard-valued stocks, they use buy-sell imbalance as the proxy of sentiment factor. We also find in cryptocurrency market, sentiment-related cryptocurrencies are concentrated in cryptocurrencies with huge return or loss, this is evidence that sentiment factor is not redundant. Assamoi, Ekponon, and Guo (2023) verify that cryptocurrency portfolios are exposed to some common risk factors in equity, currency, and commodity market. Liu, Tsyvinski, and Wu (2022) document that three notable cryptocurrency risk factors—market, size, and momentum—jointly explains the variation in cryptocurrency returns during the sample period spanning from January 2014 to August 2018. While our results align with those of Liu, Tsyvinski, and Wu (2022), we introduce an additional sentiment factor to their three-factor model. We propose a four-factor model, which incorporates market, sentiment, size, and momentum factors. We demonstrate that incorporating the sentiment factor increases the cross-sectional prediction power by approximately 13%. Additionally, our findings suggest that this four-factor model enhances the return prediction capacity in both cross-sectional tests and characteristics-based long-short strategies. In sum, our analysis highlights the significance of sentiment as a crucial common risk factor in elucidating cryptocurrency cross-sectional returns.

[4]Weekly return difference of 1.7% is reported in un-adjusted total return. This equates to an annualized total return of 140.26% when using weekly compounding.

[Insert Figure 4 Here]

Figure 4 presents an analysis of sentiment conditional returns across various cryptocurrency portfolios, categorized based on the characteristics previously discussed. Specifically, the first sub-figure focuses on the impact of market capitalization (MCAP) on portfolio performance. At the start of each week, cryptocurrencies are divided into ten groups according to their MCAP values. The week is deemed a "high sentiment week" if the $\Delta CryptoSent$ at the week's beginning is above the median $\Delta CryptoSent$ value; otherwise, it is considered a "low sentiment week." We then track the performance of these portfolios over the following week to calculate the conditional return based on sentiment for each group.

The blue bars represent the average return of portfolios during high sentiment weeks, while the orange bars indicate average returns under low sentiment conditions. The blue line highlights the difference in mean returns between high and low sentiment scenarios. Notably, portfolios not driven by momentum show a significant return differential between group 1 and group 10, indicating a pronounced sentiment effect. In contrast, for momentum-based portfolios, the most substantial sentiment-driven return disparity occurs predominantly in group 10.

This analysis underscores the significant impact of market sentiment on the performance of cryptocurrency investment strategies, affirming the significance of our constructed sentiment index in predicting conditional returns based on distinct cryptocurrency characteristics.

5 Conclusion

The growing importance of investor sentiment in financial markets, alongside the swift advancement of blockchain and cryptocurrency sectors, underscores the need to examine the relationship between investor sentiment and cryptocurrency returns more closely. In this study, we investigate the role of sentiment in explaining the cross-sectional variations in cryptocurrency returns.

We construct a sentiment index named CryptoSent. Our analyses confirm that the CryptoSent index effectively mirrors the overall sentiment of the cryptocurrency market. Following this validation, we assess the predictive strength of CryptoSent concerning the cross-sectional variations in cryptocurrency returns. Our findings indicate that cryptocurrencies that show high absolute sensitivities to changes in CryptoSent in the preceding month often yield diminished average returns in the following month and week. Utilizing a portfolio-sorted long-short strategy has yielded us an economically significant weekly return of 1.7%.

We propose a sentiment factor, denoted as CSTM, and examine its significance as a primary risk factor in the cross-sectional returns of cryptocurrencies. Our analysis indicates that a combination of four distinct factors—market, sentiment, size, and momentum—account for the cross-sectional variations in expected cryptocurrency returns. Additionally, we demonstrate that CSTM is instrumental in addressing the pronounced alphas observed in portfolios dominated by highly momentum-driven, sentiment-sensitive, or large-sized cryptocurrencies. Finally, we establish that the sentiment factor, beyond its statistical merit, also carries economic significance in elucidating eleven cryptocurrency characteristics-based long-short strategies.

Table 1: Summary Statistics.
Table 1 reports in each year, the number of coins whose market capitalization is over $100,000, the mean and median of those coins. It also reports the mean and median of daily trading price volume of those coins. The number of coins in our sample increase from 417 to in 2014 to 2981 in 2021, then decreases to 2096 in 2023. The mean (median) market capitalization ranges from 70 (0.43) million to 981 (7.5) million dollars. Mean (median) dollar price volume ranges from 342 (3.46) thousand to 288,551 (174.35) thousand dollars. All three indicators exhibit a consistent pattern, indicating that the cryptocurrency market experienced robust growth from 2014, peaked in 2021, and subsequently entered a period of cooling.

		Market Cap (million)		**Volume** (thousand)	
Year	**Number**	**Mean**	**Median**	**Mean**	**Median**
2014	417	70.42	0.43	342.05	3.46
2015	291	34.67	0.34	305.44	0.82
2016	417	54.5	0.5	619.1	1.55
2017	1090	256.85	2.09	11342.67	15.29
2018	1942	251.13	3.68	14660.19	27.32
2019	1985	160.78	1.98	41015.14	29.3
2020	2384	238.19	2.57	83654.86	59.49
2021	2981	981.87	7.5	158966.4	244.39
2022	2702	668	4.65	288551	174.35
2023	2096	541.6	4.32	50796.58	159.72

Table 2: Cryptocurrency Sentiment Index CryptoSent Components Correlation Matrix.
Table 2 presents the correlation matrix among all components: Cryptocurrency market index, market volatility, market volume, google trends, tweets discussion and number of active wallets on blockchain. CryptoSent is constructed according to Equation (2). All these components are reported in daily level and available from January 2014 to March 2023, except for tweets discussion data, which is accessible from April 2014. All components are reindexed from 0 to 100. Finally, we compute the overall CryptoSent by weighted value of these components.

Weekly Sentiment Component Correlation						
	Cryptocurrency Index	**Volatility Index**	**Volume Index**	**Google Index**	**Tweets Count**	**Active Wallet**
Crypto Index	100%					
Volatility Index	84.41%	100%				
Volume Index	91.83%	80.03%	100%			
Google Index	44.59%	54.91%	44.67%	100%		
Tweets Count	74.21%	61.28%	73.64%	49.90%	100%	
Active Wallet	78.88%	68.39%	66.87%	57.22%	68.60%	100%
CryptoSent	97.95%	92.06%	93.45%	53.46%	75.59%	80.44%

Table 3: Portfolios Sorted by Exposure to CryptoSent

Panel A displays the weekly result for portfolios categorized into five quintiles based on their unsigned exposure to sentiment, represented as $|\beta^i_{\Delta CryptoSent}|$. Each week, group 5 comprises cryptocurrencies highly responsive to $\Delta CryptoSent$ in the preceding 28 days. Group 1 consists of cryptocurrencies exhibiting a neutral response to $\Delta CryptoSent$ during the same period, Lastly, group 5-1 represents long-short sentiment portfolio. Panel B, displays the monthly (4-week) result for the portfolios categorized into five quintiles based on their unsigned exposure to sentiment, represented as $|\beta^i_{\Delta CryptoSent}|$. Each month, group 5 comprises cryptocurrencies highly responsive to $\Delta CryptoSent$ in the preceding 28 days. Group 1 consists of cryptocurrencies exhibiting a neutral response to $\Delta CryptoSent$ during the same period, Lastly, group 5-1 represents long-short sentiment portfolio.

Panel A. Sentiment Strategy Weekly Excess Return						
	Quintiles					
	1	**2**	**3**	**4**	**5**	**5-1**
$\lvert\beta^i_{\Delta CryptoSent}\rvert$	**Low**				**High**	
Mean	-0.008	0.005	-0.004	-0.001	-0.025	-0.017
t(mean)	(-1.60)	(-0.61)	(-0.58)	(-0.09)	(-3.22)***	(-2.82)***

Panel B. Sentiment Strategy Monthly (4-week) Excess Return						
	Quintiles					
	1	**2**	**3**	**4**	**5**	**5-1**
$\lvert\beta^i_{\Delta CryptoSent}\rvert$	**Low**				**High**	
Mean	0.058	0.052	0.076	0.108	0.001	-0.057
t(mean)	(1.99)**	(1.45)	(1.56)	(1.31)	(0.02)	(-2.11)**

Table 4: Size, Momentum, Volume and Volatility Strategies
This table provides statistics for size, momentum, volume, and volatility-related strategies spanning the period from 2014 to 2023. Panel A reports the mean quintile portfolio returns based on the market capitalization (MCAP), last-day price (PRC). Panel B reports the mean quintile portfolio returns based on the past one-week (R 1,0), two-week (R 2,0) and three-week (R 3,0) return measures. Panel C reports the mean quintile portfolio returns based on the price volume (PRCVOL) measure. Panel D reports the mean quintile portfolio returns based on the standard deviation of price volume (STDPRCVOL). The mean returns are the time-series averages of weekly value-weighted portfolio excess returns. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A. Size Strategy						
	Quintiles					
	1	**2**	**3**	**4**	**5**	**5-1**
MCAP	**Low**				**High**	
Mean	0.026	0.027	0.007	-0.003	-0.004	-0.03
t(mean)	(3.00)***	(1.91)*	-0.91	(-0.45)	(-0.77)	(-4.01)***
PRC	**Low**				**High**	
Mean	0.049	0.036	0.022	0.002	0.012	-0.038
t(mean)	(2.54)**	(2.87)***	(2.47)**	(-0.25)	(2.40)**	(-2.11)*

Panel B. Momentum Strategy						
	Quintiles					
	1	**2**	**3**	**4**	**5**	**5-1**
R 1, 0	**Low**				**High**	
Mean	-0.009	0.001	0.013	0.024	0.026	0.035
t(mean)	(-1.17)	-0.18	(2.25)**	(2.56)**	(2.29)**	(3.11)***
R 2, 0	**Low**				**High**	
Mean	-0.009	-0.001	0.014	0.02	0.028	0.037
t(mean)	(-1.27)	(-0.11)	(1.94)*	(2.75)***	(2.61)***	(3.41)***
R 3, 0	**Low**				**High**	
Mean	-0.005	0.001	0.008	0.023	0.03	0.035
t(mean)	(-0.66)	(-0.15)	(-1.38)	(3.02)***	(3.15)***	(3.49)***

Panel C. Volume Strategy						
	Quintiles					
	1	**2**	**3**	**4**	**5**	**5-1**
PRCVOL	**Low**				**High**	
Mean	0.042	0.021	0.026	0.017	0.012	-0.030
t(mean)	(3.11)***	(2.10)**	(2.70)***	(2.30)**	(2.46)**	(-2.48)**

Panel D. Volatility Strategy						
	Quintiles					
	1	**2**	**3**	**4**	**5**	**5-1**
STDPRCVOL	**Low**				**High**	
Mean	0.036	0.048	0.024	0.021	0.012	-0.024
t(mean)	(2.86)***	(1.91)*	(2.63)***	(2.73)***	(2.42)**	(-2.19)**

Table 5: Cryptocurrency Factors Model with Sentiment Factor.

Table 5 reports results on the cryptocurrency factor adjustments of the successful long-short strategies. CMKT is the cryptocurrency excess market return, CSTM is the cryptocurrency sentiment factor, CSMB is the cryptocurrency size factor, and CMOM is the cryptocurrency momentum factor. t-Statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. Model (1), (2) and (3) of table 4 presents different two-factor models with the CSTM, CSMB or CMOM respectively. Model (4) presents three-factor model proposed by Liu, Tsyvinski, and Wu (2022). Model (5) introduces four-factor model we propose, incorporating CMKT, CSTM, CSMB and CMOM.

Strategy	Model	Cons	Cons t	CMKT	CMKT t	CSMB	CSMB t	CMOM	CMOM t	CSTM	CSTM t	R^2	M.A.E
$\|\beta_{SENT}\|$	1	-0.018***	(-2.88)	0.094**	(2.01)	-0.019***	(-0.48)					0.009	0.09
	2	-0.021***	(-3.37)	0.099**	(2.12)			0.074**	(1.97)			0.017	0.089
	3	-0.004	(-1.07)	0.007	(0.23)					0.662***	(29.16)	0.648	0.045
	4	-0.020***	(-3.22)	0.099**	(2.11)	-0.013	(-0.32)	0.073*	(1.93)			0.017	0.09
	5	-0.006	(-1.59)	0.009	(0.32)	0.032	(1.35)	0.036	(1.60)	0.662***	(29.11)	0.651	0.045
MCAP	1	-0.01	(-1.60)	0.042	(0.91)	-0.614***	(-15.70)					0.346	0.071
	2	-0.028***	(-3.69)	0.043	(0.74)			-0.062	(-1.35)			0.005	0.094
	3	-0.033***	(-4.31)	0.061	(1.07)					-0.111**	(-2.39)	0.013	0.093
	4	-0.006	(-1.00)	0.035	(0.76)	-0.623***	(-16.00)	-0.110***	(-2.96)			0.358	0.07
	5	-0.009	(-1.52)	0.055	(1.2)	-0.633***	(-16.49)	-0.102***	(-2.78)	-0.147***	(-3.96)	0.379	0.069
PRC	1	-0.022	(-1.21)	-0.606***	(-4.51)	-0.095***	(-0.84)					0.043	0.131
	2	-0.018	(-0.99)	-0.62***	(-4.63)			-0.236**	(-2.20)			0.051	0.136
	3	-0.033*	(-1.87)	-0.559***	(-4.18)					-0.355***	(-3.28)	0.063	0.128
	4	-0.014	(-0.75)	-0.622***	(-4.64)	-0.116	(-1.02)	-0.245**	(-2.27)			0.054	0.135
	5	-0.021	(-1.17)	-0.574***	(-4.31)	-0.139***	(-1.24)	-0.226**	(-2.11)	-0.35***	(-3.23)	0.074	0.129
R 1,0	1	0.039***	(3.31)	0.12	(1.38)	-0.143***	(-1.95)					0.012	0.134
	2	0.018*	(1.66)	0.154*	(1.87)			0.516***	(7.82)			0.119	0.121
	3	0.033***	(2.84)	0.127	(1.45)					-0.048	(-0.67)	0.005	0.134
	4	0.022*	(1.94)	0.153*	(1.86)	-0.1	(-1.44)	0.508***	(7.69)			0.123	0.121
	5	0.020*	(1.75)	0.164**	(1.99)	-0.106	(-1.53)	0.513***	(7.75)	-0.087	(-1.30)	0.126	0.122

Strategy	Model	Cons	Cons t	CMKT	CMKT t	CSMB	CSMB t	CMOM	CMOM t	CSTM	CSTM t	R^2	M.A.E
R 2,0	1	0.041***	(3.63)	0.119	(1.42)	-0.107***	(-1.53)					0.009	0.131
	2	0.015	(1.54)	0.165**	(2.28)			0.727***	(12.48)			0.253	0.104
	3	0.038***	(3.47)	0.112	(1.33)					0.058	(0.85)	0.006	0.129
	4	0.017*	(1.67)	0.165**	(2.27)	-0.047	(-0.76)	0.723***	(12.37)			0.254	0.104
	5	0.016	(1.58)	0.163**	(2.23)	-0.046	(-0.75)	0.723***	(12.33)	0.01	(0.16)	0.254	0.104
R 3,0	1	0.036***	(3.45)	0.036	(0.46)	-0.038***	(-0.58)					0.001	0.132
	2	0.01	(1.18)	0.088	(1.41)			0.818***	(16.4)			0.365	0.089
	3	0.036***	(3.53)	0.027	(0.34)					0.071	(1.12)	0.003	0.132
	4	0.009	(1.02)	0.088	(1.41)	0.031	(0.59)	0.820***	(16.38)			0.366	0.089
	5	0.009	(1.07)	0.085	(1.36)	0.033	(0.62)	0.819***	(16.32)	0.022	(0.44)	0.366	0.089
PRCVOL	1	-0.014	(-1.13)	-0.144	(-1.60)	-0.382***	(-5.03)					0.056	0.124
	2	-0.018	(-1.46)	-0.159*	(-1.74)			-0.277***	(-3.77)			0.034	0.13
	3	-0.029**	(-2.40)	-0.123	(-1.32)					-0.14*	(-1.86)	0.012	0.128
	4	-0.003	(-0.29)	-0.164*	(-1.85)	-0.408***	(-5.45)	-0.308***	(-4.31)			0.092	0.126
	5	-0.007	(-0.55)	-0.143	(-1.61)	-0.418***	(-5.59)	-0.300***	(-4.21)	-0.149**	(-2.06)	0.1	0.125
STD-PRCVOL	1	-0.007	(-0.60)	-0.204**	(-2.51)	-0.395***	(-5.78)					0.078	0.114
	2	-0.01	(-0.94)	-0.22***	(-2.68)			-0.301***	(-4.56)			0.054	0.121
	3	-0.023**	(-2.08)	-0.18**	(-2.14)					-0.16**	(-2.36)	0.024	0.117
	4	0.005	(0.42)	-0.225***	(-2.85)	-0.423***	(-6.35)	-0.334***	(-5.25)			0.129	0.118
	5	0.001	(0.08)	-0.202**	(-2.56)	-0.435***	(-6.54)	-0.324***	(-5.12)	-0.169***	(-2.64)	0.142	0.117

Table 6: Average Weekly Percent Excess Returns for Portfolios Formed on Sentiment and Momentum. Each week, all available cryptocurrencies are allocated to five sentiment groups (Neutral to Sensitive) based on their last 28 days' unsigned exposures on sentiment ($|\beta^i_{\Delta CryptoSent}|$). Cryptocurrencies are also allocated independently to five momentum groups (Low to High) based on their past 3-week returns. The intersections of the two sorts produce 5×5 value-weight Sentiment-Momentum portfolios. We test the three-factor and four-factor model regression results of all these Sentiment-Momentum in Panel A and Panel B. Panel C reports the sentiment-sensitivity concentration in momentum (R 3,0) strategies. We report the mean of each quantile portfolios' average exposure on sentiment ($|\beta^i_{\Delta CryptoSent}|$) weighted by market capitalization.

Regressions for 5*5 value-weight Sentiment-Momentum portfolios										
Momentum →	Low	2	3	4	High	Low	2	3	4	High
Panel A: Three-factor (CMKT, CSMB, CMOM) regression intercepts										
$R(t) - R_f(t) = \alpha + \beta_{cmkt}CMKT + \beta_{size}CSMB + \beta_{momentum}CMOM + e(t)$										
Sentiment ↓	α					$t(\alpha)$				
Neutral	-0.02	-0.009	-0.003	0.008	0.005	-3.171	-1.587	-0.704	1.359	0.37
2	-0.007	-0.008	-0.005	0.006	0.004	-0.812	-1.329	-0.901	0.584	0.361
3	-0.014	-0.011	0.002	-0.003	0.01	-2.045	-1.554	0.248	-0.463	1.168
4	-0.008	0.014	-0.005	0.004	0.006	-1.062	0.77	-0.766	0.549	0.689
Sensitive	-0.011	0.004	-0.018	-0.007	-0.018	-1.152	0.341	-2.235	-0.844	-1.723
Sentiment ↓	R^2					$S(e)$				
Neutral	0.358	0.302	0.453	0.354	0.191	0.131	0.117	0.092	0.118	0.26
2	0.316	0.369	0.436	0.239	0.223	0.178	0.126	0.113	0.203	0.21
3	0.387	0.307	0.272	0.298	0.249	0.146	0.142	0.163	0.144	0.183
4	0.256	0.079	0.334	0.279	0.28	0.164	0.386	0.129	0.155	0.179
Sensitive	0.221	0.155	0.226	0.193	0.219	0.189	0.238	0.16	0.172	0.215
Panel B: Four-factor model regression										
$R(t) - R_f(t) = \alpha + \beta_{sentiment}CSTM + \beta_{cmkt}CMKT + \beta_{size}CSMB + \beta_{momentum}CMOM + e(t)$										
Sentiment ↓	α					$t(\alpha)$				
Neutral	-0.019	-0.008	-0.002	0.008	0.005	-2.941	-1.462	-0.533	1.387	0.398
2	-0.003	-0.006	-0.003	0.007	0.007	-0.377	-0.914	-0.543	0.693	0.673
3	-0.009	-0.004	0.004	-0.001	0.013	-1.287	-0.671	0.522	-0.109	1.465
4	-0.005	0.02	-0.001	0.007	0.01	-0.666	1.045	-0.221	0.9	1.173
Sensitive	-0.005	0.01	-0.014	-0.002	0.004	-0.549	0.849	-1.789	-0.297	0.656

Sentiment ↓	β_{cmkt}					$t(\beta_{cmkt})$				
Neutral	0.636	0.574	0.63	0.663	0.708	13.558	13.686	19.072	15.701	7.608
2	0.69	0.7	0.74	0.847	0.703	10.962	15.648	18.406	11.646	9.382
3	0.736	0.656	0.735	0.699	0.688	14.81	13.654	12.693	13.64	10.48
4	0.622	0.766	0.673	0.715	0.721	10.741	5.579	14.859	12.965	11.407
Sensitive	0.641	0.705	0.626	0.607	0.678	9.724	8.355	11.045	9.971	13.71

Sentiment ↓	$\beta_{sentiment}$					$t(\beta_{sentiment})$				
Neutral	0.064	0.028	0.033	0.011	0.018	1.691	0.824	1.245	0.313	0.24
2	0.176	0.113	0.09	0.053	0.149	3.444	3.089	2.779	0.901	2.465
3	0.264	0.29	0.096	0.118	0.118	6.54	7.431	2.025	2.843	2.216
4	0.141	0.235	0.159	0.124	0.191	2.98	2.106	4.331	2.775	3.722
Sensitive	0.257	0.268	0.178	0.207	1.028	4.806	3.902	3.862	4.164	25.609

Sentiment ↓	β_{size}					$t(\beta_{size})$				
Neutral	0.09	0.04	0.03	0.081	0.271	2.262	1.125	1.071	2.293	3.464
2	0.351	0.116	0.082	0.147	0.337	6.629	3.076	2.44	2.4	5.368
3	0.167	0.053	0.101	0.087	0.006	3.985	1.305	2.079	2.011	0.109
4	-0.104	0.215	0.025	0.099	-0.151	-2.139	1.857	0.618	2.145	-2.83
Sensitive	-0.003	0.166	0.15	0.099	0.074	-0.058	2.352	2.917	1.926	1.769

Sentiment ↓	$\beta_{momentum}$					$t(\beta_{momentum})$				
Neutral	-0.27	-0.072	-0.065	0.042	0.513	-6.998	-2.132	-2.468	1.237	6.857
2	-0.309	-0.094	-0.059	0.101	0.263	-6.12	-2.611	-1.825	1.729	4.384
3	-0.29	-0.15	-0.056	0.035	0.346	-7.262	-3.851	-1.2	0.856	6.569
4	-0.261	-0.167	-0.066	-0.006	0.301	-5.552	-1.51	-1.805	-0.134	5.929
Sensitive	-0.287	-0.118	0.007	0.029	0.22	-5.436	-1.718	0.154	0.579	5.551

Sentiment ↓	R^2					$S(e)$				
Neutral	0.362	0.303	0.455	0.354	0.191	0.131	0.118	0.092	0.118	0.26
2	0.333	0.382	0.446	0.24	0.233	0.176	0.125	0.112	0.203	0.209
3	0.439	0.381	0.279	0.31	0.257	0.139	0.135	0.162	0.143	0.183
4	0.27	0.088	0.36	0.29	0.301	0.162	0.385	0.127	0.154	0.177
Sensitive	0.258	0.182	0.251	0.223	0.676	0.185	0.235	0.158	0.169	0.139

Panel C. Momentum Quintiles' Weighted Average Exposures on Sentiment $\lvert\beta^{i}_{\Delta CryptoSent}\rvert$					
	Quintiles				
	1	**2**	**3**	**4**	5
R 3,0	**Low**				**High**
Mean	0.090	0.046	0.036	0.037	0.081

Table 7: Average Weekly Percent Excess Returns for Portfolios Formed on Sentiment and Size.
Each week, all available cryptocurrencies are allocated to five sentiment groups (Neutral to Sensitive) based on their last 28 days' unsigned exposures on sentiment ($|\beta^i_{\Delta CryptoSent}|$). Cryptocurrencies are also allocated independently to five size groups (Small to Big) based on their market capitalizations. The intersections of the two sorts produce 5×5 value-weight Sentiment-Size portfolios. We test the three-factor and four-factor model regression results of all these Sentiment-Size in Panel A and Panel B. Panel C reports the sentiment-sensitivity concentration in size (MCAP) strategies. We report the mean of each quintile portfolios' average exposure on sentiment ($|\beta^i_{\Delta CryptoSent}|$) weighted by market capitalization.

Regressions for 5*5 value-weight Sentiment-Momentum portfolios

Momentum →	Low	2	3	4	High	Low	2	3	4	High
Panel A: Three-factor (CMKT, CSMB, CMOM) regression intercepts										
$R(t) - R_f(t) = \alpha + \beta_{cmkt}CMKT + \beta_{size}CSMB + \beta_{momentum}CMOM + e(t)$										
Sentiment ↓	α					$t(\alpha)$				
Neutral	0.126	-0.009	0.001	-0.005	-0.001	0.649	-1.316	0.119	-0.604	-0.327
2	-0.01	0.008	-0.009	0.001	0.008	-0.759	0.865	-1.343	0.191	1.017
3	-0.001	0	0.001	-0.005	0.001	-0.133	0.051	0.075	-0.89	0.122
4	0.005	0.009	0	-0.008	0.009	0.653	0.927	-0.038	-1.187	1.163
Sensitive	0.005	-0.007	0.005	-0.003	-0.031	0.573	-0.791	0.538	-0.287	-3.591
Sentiment ↓	R^2					$S(e)$				
Neutral	0.007	0.343	0.337	0.206	0.55	4.005	0.137	0.125	0.182	0.074
2	0.346	0.249	0.323	0.33	0.277	0.281	0.192	0.144	0.136	0.157
3	0.409	0.39	0.309	0.349	0.326	0.182	0.136	0.167	0.121	0.137
4	0.407	0.234	0.154	0.367	0.301	0.152	0.192	0.231	0.137	0.159
Sensitive	0.338	0.264	0.205	0.196	0.252	0.193	0.175	0.204	0.198	0.175
Panel B: Four-factor model regression										
$R(t) - R_f(t) = \alpha + \beta_{sentiment}CSTM + \beta_{cmkt}CMKT + \beta_{size}CSMB + \beta_{momentum}CMOM + e(t)$										
Sentiment ↓	α					$t(\alpha)$				
Neutral	0.134	-0.005	0.002	-0.004	-0.002	0.683	-0.819	0.377	-0.412	-0.499
2	-0.006	0.01	-0.007	0.004	0.008	-0.419	1.113	-1.061	0.532	1.081
3	0.002	0.001	0.002	-0.002	0.004	0.214	0.202	0.242	-0.343	0.628
4	0.008	0.011	0.003	-0.004	0.013	1.093	1.183	0.297	-0.654	1.629
Sensitive	0.006	-0.003	0.013	0.008	-0.017	0.665	-0.413	1.335	0.888	-2.505

Sentiment ↓	β_{cmkt}					$t(\beta_{cmkt})$				
Neutral	1.484	0.65	0.635	0.662	0.628	1.036	13.422	14.222	10.163	23.756
2	0.753	0.664	0.697	0.684	0.737	7.493	9.736	13.609	14.202	13.136
3	0.724	0.743	0.789	0.641	0.709	11.227	15.353	13.206	15.086	14.616
4	0.761	0.639	0.669	0.722	0.722	14.138	9.332	8.158	14.991	12.852
Sensitive	0.692	0.611	0.717	0.67	0.673	10.009	9.886	10.21	10.275	13.318

Sentiment ↓	$\beta_{sentiment}$					$t(\beta_{sentiment})$				
Neutral	0.359	0.147	0.075	0.075	-0.029	0.309	3.703	2.059	1.416	-1.359
2	0.215	0.113	0.091	0.103	0.026	2.629	2.029	2.18	2.647	0.567
3	0.135	0.046	0.065	0.15	0.147	2.563	1.175	1.33	4.352	3.741
4	0.152	0.113	0.166	0.155	0.173	3.467	2.029	2.48	3.959	3.774
Sensitive	0.041	0.147	0.345	0.488	0.661	0.733	2.935	6.053	9.223	15.986

Sentiment ↓	β_{size}					$t(\beta_{size})$				
Neutral	0.284	0.308	0.201	0.203	-0.004	0.236	7.57	5.336	3.714	-0.181
2	1.147	0.433	0.272	0.193	0.052	13.636	7.554	5.901	4.768	1.107
3	0.766	0.313	0.264	0.147	0	14.015	7.688	4.934	4.11	0.004
4	0.49	0.419	0.27	0.258	-0.209	10.816	7.281	3.91	6.373	-4.42
Sensitive	0.677	0.414	0.212	0.128	-0.001	11.693	7.961	3.585	2.343	-0.024

Sentiment ↓	$\beta_{momentum}$					$t(\beta_{momentum})$				
Neutral	1.627	0.075	0.062	0.06	-0.03	1.415	1.887	1.719	1.146	-1.416
2	-0.053	-0.013	0.04	0.04	-0.015	-0.646	-0.243	0.966	1.039	-0.33
3	0.007	0.055	0.161	0.008	0.029	0.141	1.42	3.34	0.229	0.749
4	-0.024	0.097	0.007	-0.006	0.059	-0.547	1.767	0.111	-0.153	1.293
Sensitive	0.018	0.168	0.069	0.092	-0.013	0.33	3.398	1.224	1.765	-0.306

Sentiment ↓	R^2					$S(e)$				
Neutral	0.007	0.362	0.344	0.21	0.552	4.009	0.135	0.125	0.182	0.074
2	0.355	0.255	0.33	0.34	0.278	0.279	0.191	0.143	0.135	0.157
3	0.417	0.392	0.311	0.374	0.346	0.18	0.136	0.167	0.119	0.135
4	0.422	0.24	0.165	0.388	0.322	0.151	0.192	0.23	0.135	0.157
Sensitive	0.339	0.278	0.263	0.32	0.525	0.193	0.173	0.197	0.183	0.139

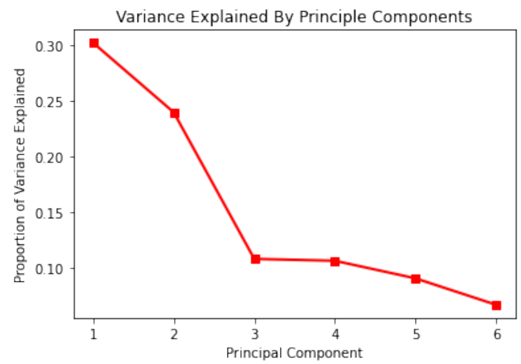
Panel C. Size Quintiles' Weighted Average Exposures on Sentiment $\lvert\beta^{i}_{\Delta CryptoSent}\rvert$					
	Quintiles				
	1	**2**	**3**	**4**	5
MCAP	**Low**				**High**
Mean	0.121	0.117	0.104	0.093	0.020

Table 8: Fama and Macbeth (1973) Cross-Sectional Regression.
Table 8 reports Fama-MacBeth regression results. For each cryptocurrency, each of its characteristics is first sorted into five portfolios at the end of each week, and the portfolio rank numbers are used as explanatory variables. These characteristics are market beta (β_{CMKT}), sentiment beta ($|\beta^i_{\Delta CryptoSent}|$), market capitalization (MCAP), last-day price (PRC), and three-week (R 3,0) return.

Panel A: One-Factor Model						
Model	**Intercept**	β_{CMKT}	$\lvert\beta^i_{\Delta CryptoSent}\rvert$	**MCAP**	**R 3,0**	$\bar{R}^2$
(1)	0.012		-0.005			1.55%
	(2.16)		(-5.80)			
(2)	0.053			-0.009		1.58%
	(2.09)			(-1.59)		
(3)	-0.007				0.002	2.31%
	(-1.17)				(1.75)	
Panel B: Two-Factor Model						
Model	**Intercept**	β_{CMKT}	$\lvert\beta^i_{\Delta CryptoSent}\rvert$	**MCAP**	**R 3,0**	$\bar{R}^2$
(4)	0.015	-0.001	-0.005			3.12%
	(2.76)	(-0.89)	(-6.05)			
(5)	0.038	0.003		-0.007		3.09%
	(2.11)	(0.801)		(-1.48)		
(6)	-0.005	-0.001			0.002	3.82%
	(-0.81)	(-0.84)			(1.69)	
Panel C: Multiple-Factor Model						
Model	**Intercept**	β_{CMKT}	$\lvert\beta^i_{\Delta CryptoSent}\rvert$	**MCAP**	**R 3,0**	$\bar{R}^2$
(7)	0	-0.001	-0.005	0.003		4.79%
	(-0.016)	(-0.64)	(-5.66)	(1.48)		
(8)	0.007	-0.001	-0.005		0.002	5.38%
	(1.13)	(-0.97)	(-6.33)		(2.07)	
(9)	-0.009		-0.005	0.003	0.002	5.46%
	(-0.72)		(-5.65)	(1.49)	(1.85)	
(10)	-0.026	-0.001		0.005	0.002	5.51%
	(-2.05)	(-0.50)		(2.25)	(1.31)	
(11)	-0.003	-0.001	-0.005	0.003	0.002	7.02%
	(-0.21)	(-0.82)	(-6.02)	(1.17)	(1.21)	

Table 9: PCA Analysis of Cryptocurrency Returns.
Table 9 reports results of principle component analysis of the 8 long-short strategies. Panel A plots the variance explained by the first 6 principal components respectively. Panel B reports the correlation matrix of the first 4 principal components, the cryptocurrency market portfolio excess return (CMKT), cryptocurrency sentiment factor (CSTM), cryptocurrency size factor (CSMB) and cryptocurrency momentum factor (CMOM).

Panel A. Variance Explained



Panel B. Correlation

	PC 1	PC 2	PC 3	PC 4	CMKT	CSTM	CSMB	CMOM
PC 1	-							
PC 2	0.00%	-						
PC 3	0.00%	0.00%	-					
PC 4	0.00%	0.00%	0.00%	-				
CMKT	13.65%	2.14%	-14.30%	-21.30%	-			
CSTM	15.93%	20.01%	52.36%	-49.97%	10.71%	-		
CSMB	5.69%	36.36%	1.59%	-2.27%	-0.59%	-6.96%	-	
CSMB	50.54%	-8.03%	-6.26%	-7.02%	-5.06%	5.56%	-7.97%	-

Figure 1: Main Cryptocurrencies.
Figure 1 plots the cumulative dollar values of 1-dollar investments in cryptocurrency market index, Bitcoin, Ripple and Ethereum. Bitcoin and Ripple are plotted from the beginning of 2014. Ethereum is plotted from August 2015.

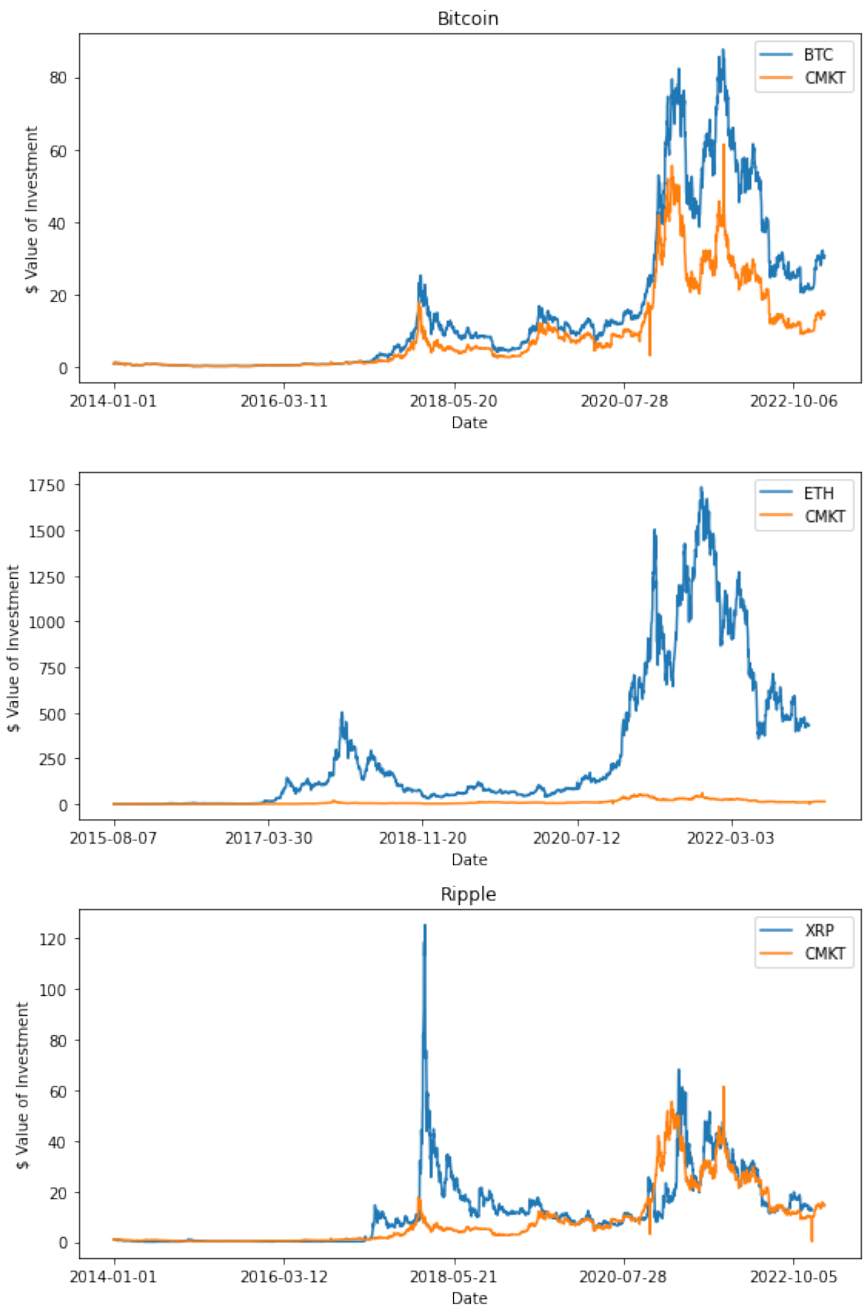
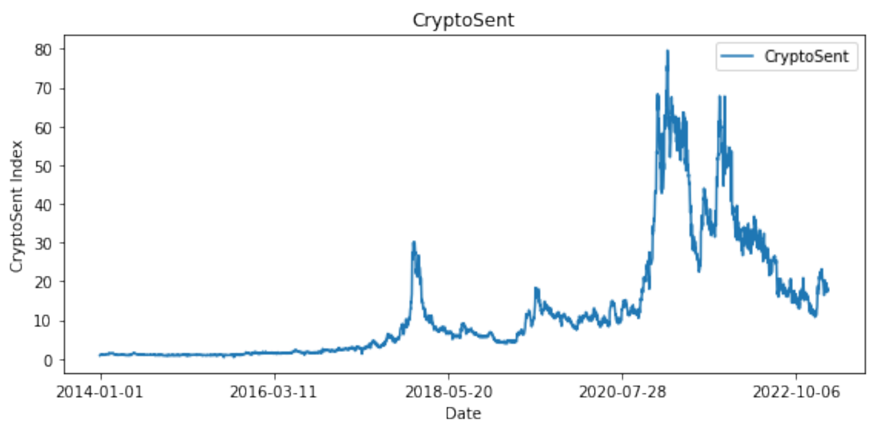


Figure 2: Cryptocurrency Sentiment Index CryptoSent Time Series Plot.
Figure 2 Panel A plots the time series of Sentiment Index CryptoSent, including the cryptocurrency market index, market volatility, market volume, google trends, tweets discussion and number of active wallets on blockchain. The Cryptosent is daily level and available from January 2014 to March 2023. Figure 2 Panel B also includes some events in cryptocurrency market. The vertical lines represent the shocks in cryptocurrency market.

Panel A



Panel B

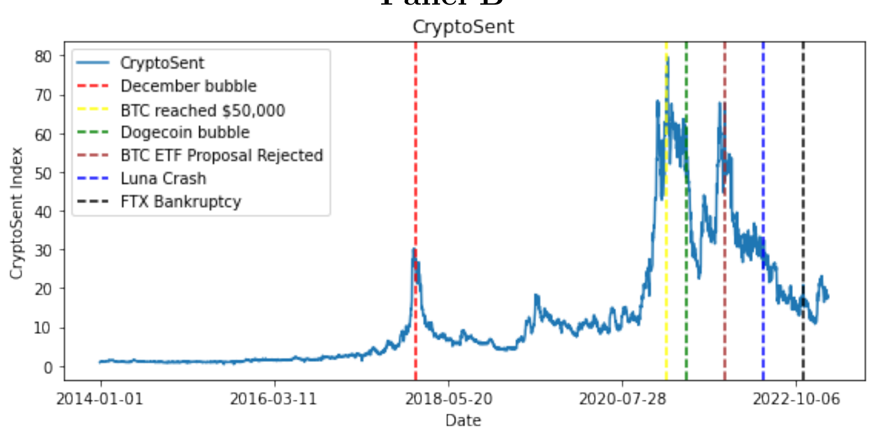


Figure 3: Cryptocurrency Sentiment Index CryptoSent Components.
Figure 3 plots the components of Sentiment Index CryptoSent, including the cryptocurrency market index, market volatility, market volume, google trends, tweets discussion and number of active wallets on blockchain. All these components are reported in daily level and available from January 2014 to March 2023, except for tweets discussion data, which is accessible from April 2014. Each of these components is presented as an index, transformed from its original values to a standardized scale ranging from 0 to 100.

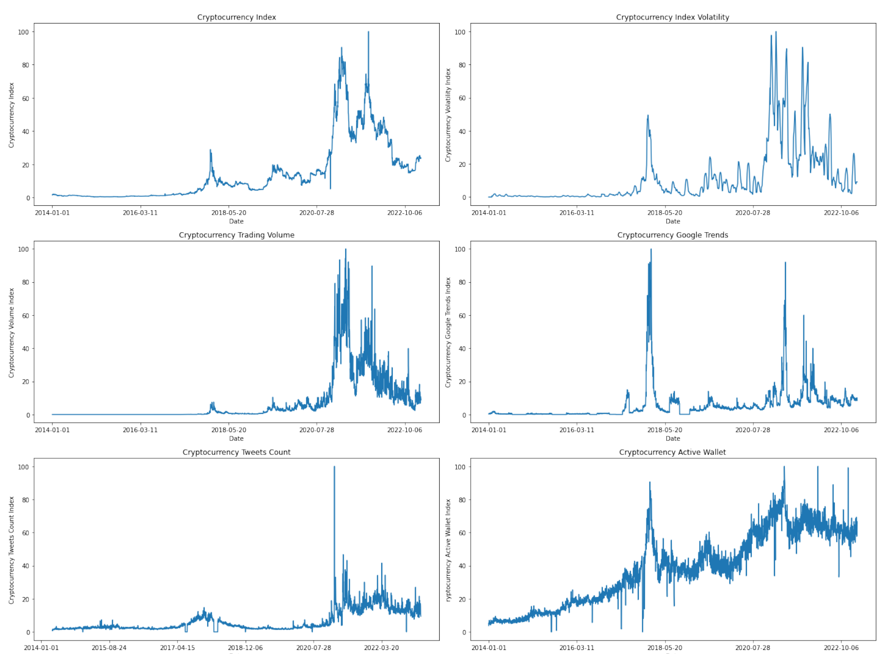
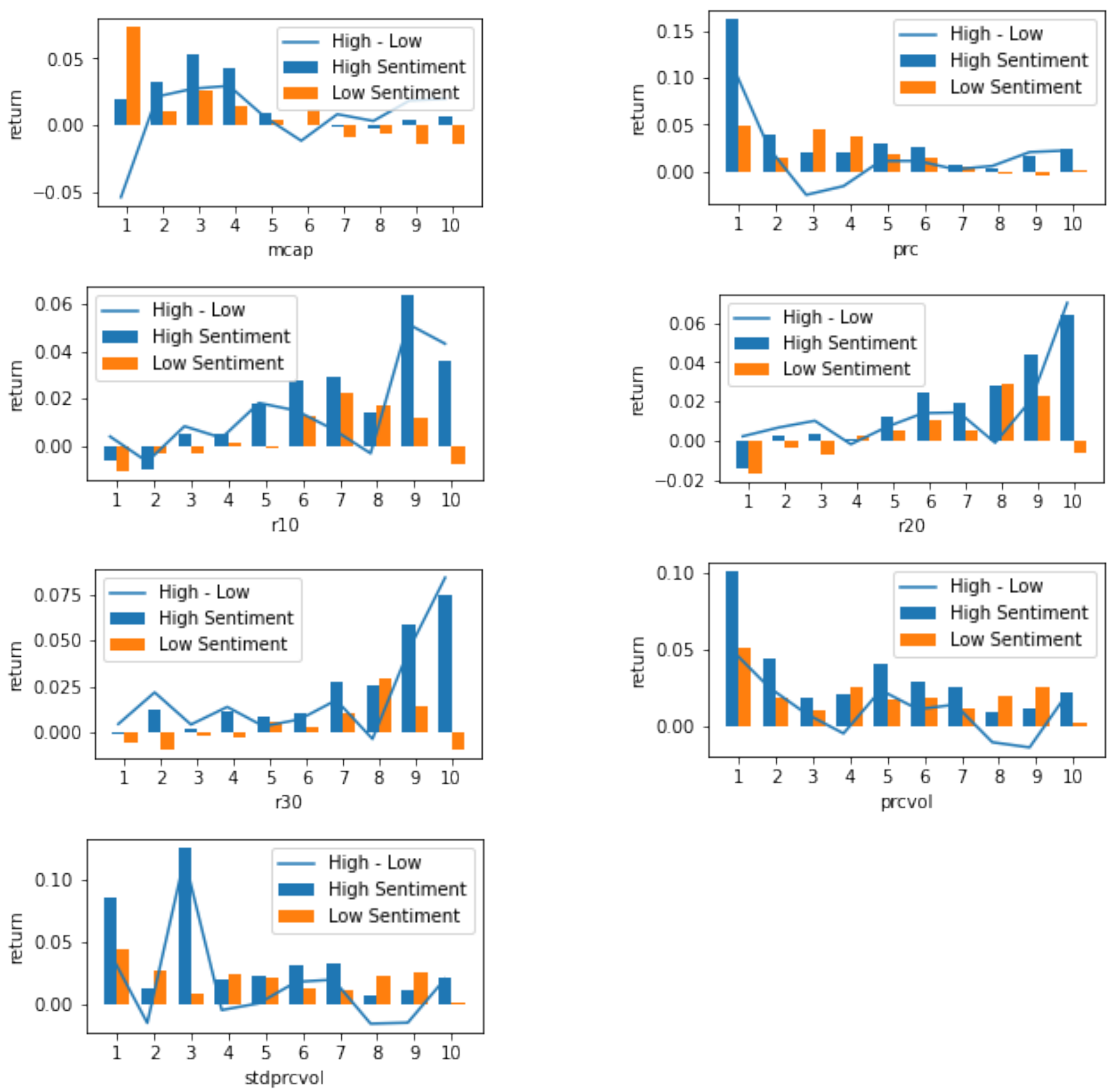


Figure 4: Long Short Portfolio Strategy Conditional on Long-Short Leg. Figure 4 presents the future weekly return by sentiment index and firm characteristics. Each week, we categorize the sentiment index as high or low based on whether the latest $\Delta CryptoSent$ is above or below its median, respectively. Cryptocurrencies are then sorted into 10 quintiles according to their characteristics. These characteristics are market capitalization (MCAP), last-day price (PRC), past one-week (R 1,0), two-week (R 2,0) and three-week (R 3,0) return, price volume (PRCVOL) and standard deviation of price volume (STDPRCVOL). The orange bars are returns following low sentiment, and the blue bars are returns following high sentiment. The solid blue line is the difference.



Appendix A.Robustness of CryptoSent Construction: Portfolios Sorted by Exposure to Equal-Weighted CryptoSent

As detailed in Section 3.2, we employ the construction methodology outlined in Equation (2) because this approach is more effective in capturing significant market phenomena, such as major events, shocks, or crashes, in the cryptocurrency market. To further validate this, we test the robustness of the CryptoSent construction, our proposed sentiment analysis framework, in Appendix A. All procedures are same as described in Section 3.2, except that we change the construction of CryptoSent in Equation (2) to equal-weighted average of Crypto Index, Volatility Index, Volume Index and $Social\ Media\&Blockchain\ Adoption$. We next report our portfolio sort results in the following Table 10.

Table 10: Portfolios Sorted by Exposure to Equal-weighted CryptoSent.
Table 10 displays the weekly result for portfolios categorized into five quintiles based on their unsigned exposure to sentiment, represented as $|\beta^i_{\Delta CryptoSent}|$. Each week, group 5 comprises cryptocurrencies highly responsive to $\Delta CryptoSent$ in the preceding 28 days. Group 1 consists of cryptocurrencies exhibiting a neutral response to $\Delta CryptoSent$ during the same period, Lastly, group 5-1 represents long-short sentiment portfolio.

Sentiment Strategy Weekly Excess Return						
	Quintiles					
	1	**2**	**3**	**4**	**5**	**5-1**
$\lvert\beta^i_{\Delta CryptoSent}\rvert$	**Low**				**High**	
Mean	0.055	0.054	0.049	0.076	0.008	-0.047
t(mean)	(3.84)***	(2.94)***	(2.58)**	(2.44)**	(0.36)	(-2.95)***

From Table 10, we conclude that our main result remains consistent: the sentiment long-short portfolio exhibits a significant negative return of -4.7% in the immediate subsequent week. This finding proves that our construction methodology for the sentiment index, CryptoSent, is robust.

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