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)[14], 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)[16], 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)[13], Canayaz, Cao, Nguyen, and Wang (2023)[6], Philippas, Rjiba, Guesmi, and Goutte (2019)[15], as well as Liu and Tsyvinski (2021)[11], among others, have documented that Bitcoin trading is heavily influenced by investor sentiment.

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[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.

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.

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)[6] use social media sentiment to predict the cryptocurrency returns. In stock markets, Baker, and Wurgler (2006)[3] 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)[1] 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)[18] 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)[10] 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)[19] verify that cryptocurrency portfolios are exposed to some common risk factors in equity, currency, and commodity market. Liu, Tsyvinski, and Wu (2022)[12] 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) [12], 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

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

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.

The rest of this paper is organized as follows. First, we provide an overview of the cryptocurrency market. Second, we demonstrate our cryptocurrency sentiment index construction and return prediction. Third, we present cryptocurrency three factor model and cross-sectional analysis results. Finally, we conclude the paper.

2. Cryptocurrency Market Overview

2.1. Data

We collect the data from CoinMarketCap daily snapshot, CoinMarketCap started to prepare daily snapshots of cryptocurrencies since 2013. Our dataset covers time period from January 2014 to February 2023.

CoinMarketCap is a website that provides information on the market capitalization, price, volume, and other data for thousands of cryptocurrencies. It was launched in 2013 and has become one of the most popular cryptocurrency market data platforms. CoinMarketCap provides real-time data on the prices, trading volume, and market capitalization of cryptocurrencies across a variety of exchanges. For each cryptocurrency on the website, its price is calculated by taking the volume-weighted average of all prices reported on each market. A cryptocurrency needs to meet a list of criteria to be listed, such as being traded on a public exchange with an application programming interface (API) that reports the last traded price and the last 24-hour trading volume and having nonzero trading volume on at least one supported exchange so that a price can be determined.

2.2. Cryptocurrency Market Overview

We use daily close prices to construct weekly coin returns. Specifically, we divide each year into 52 weeks. The first week of the year consists of the first seven days of the year. The first 51 weeks of the year consist of seven days each and the last week of the year consists of the last eight days of the year. Our sample includes 1,827 coins from the beginning of 2014 to July 2020. The trading volume data became available in the last week of 2013, and thus our sample period starts from the beginning of 2014. We require that the coins have information on price, volume, and market capitalization. To address the issue of illiquidity in cryptocurrency trading, we have excluded coins from our dataset that have a market capitalization of less than $100,000[5].

[Insert Table 1 Here]

Summary statistics are presented in Table 1. 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.

We next construct a cryptocurrency market return as the value-weighted return of all underlying available coins. The cryptocurrency excess market return (CMKT) is constructed as the difference between the cryptocurrency market return and the risk-free rate measured by the

[5] Given the market capitalization characteristics of cryptocurrencies, applying this filter results in a minimal impact on the representativeness of our dataset.

one-month Treasury bill rate. We draw the time-series graph of CMKT and other 3 main cryptocurrencies in the market Bitcoin, Ripple, and Ethereum (Ethereum was initiated in 2015). The values are all reported as the U.S. dollar value investing one dollar from the inception of the given cryptocurrency to facilitate comparison.

[Insert Figure 1 Here]

Figure 1 plots the cumulative dollar wealth of 1-dollar investments in cryptocurrency market index, Bitcoin, Ripple and Ethereum. Bitcoin earned more than 80 times revenue in 2021 and highly correlated with the cryptocurrency market index. Ripple reached its peak at the beginning of 2018. Ethereum has earned the most abnormal revenue in 2021 due to the popularity of WEB 3.0.

3. Sentiment Index Construction and Expected Cryptocurrency Returns

3.1. Sentiment Index Construction

The sentiment factor, also known as investor sentiment, is an important aspect of finance as it can significantly impact financial markets and investment decisions. Sentiment refers to the overall mood, emotions, and attitudes of investors and market participants towards a particular financial asset, market, or the economy. Sentiment plays a significant role in driving market volatility. During periods of positive sentiment, investors tend to be optimistic, leading to increased buying activity and upward price movements. Conversely, during times of negative sentiment, fear and pessimism dominate, resulting in selling pressure and downward price movements. Sentiment-driven volatility can present both risks and opportunities for investors.

Makarov and Schoar (2021)[13], Canayaz, Cao, Nguyen, and Wang (2023)[6], Philippas, Rjiba, Guesmi, and Goutte (2019)[15], as well as Liu and Tsyvinski (2021)[11] have documented the role of investor sentiment in influencing cryptocurrency returns. Given the role that sentiment plays in the cryptocurrency market, it's natural for investors and traders to monitor indicators such as news, social media discussions, and other market sentiment analysis tools. By understanding and analyzing sentiment, they can gain insights into market trends, anticipate shifts in investor behavior, and make more informed trading decisions in the crypto market.

Previous sentiment literatures have predominantly concentrated on some specific cryptocurrencies such as Bitcoin and Ethereum. One of our contributions is constructing a comprehensive index, denoted as CryptoSent, designed to represent the sentiment across the entire cryptocurrency market. We plot CryptoSent as in the following Figure 2.

[Insert Figure 2 Here]

Figure 2 Panel A is the time series of Sentiment Index CryptoSent from January 2014 to March 2023, including the cryptocurrency market index, market volatility, market volume, google trends, tweets discussion and number of active wallets on blockchain. Figure 2 Panel B also includes some events in cryptocurrency market. The vertical lines represent the shocks in cryptocurrency market. The CryptoSent started at a low level in 2014 when the cryptocurrency market had not yet garnered significant investments. It had upward trends until 2021, where they collectively peaked before gradually cooling down. The CryptoSent also captures some major shocks happened to cryptocurrency market. On 2017 December 17, Bitcoin reached a new all-time high of $19,783 and then fell of 45% from its peak within a week. On 2021 February 16, Bitcoin reached $50,000 for the first time. Before 2021 May 19, the market is quite high due to several good news from Coinbase went public on NASDAQ and the popularity of meme tokens. The Dogecoin increased to 20,000% of value in one year. On May 19, the doge Dogecoin bubble burst. This was partly in response to Elon Musk's announcement that Tesla would suspend payments using the Bitcoin network due to environmental concerns, along with an announcement from the People's Bank of China reiterating that digital currencies cannot be used for payments. In 2021 November, there was some rumor that SEC would approve Bitcoin ETF, but on November 11, SEC confirmed the rejection of Bitcoin ETF. In May 2022, the algorithmic stable coin TerraUSD was unpegged to the U.S dollar, which finally lead its back assets Luna crashed. In November 2022, the third-largest cryptocurrency exchange FTX collapse caused by a spike in customer withdrawals that exposed an $8 billion hole in FTX's accounts. All these major shocks are captured by our CryptoSent in the figure.

Our CryptoSent encompasses various components, including the cryptocurrency market index, market volatility, market volume, google trends, tweets discussion and number of active wallets on blockchain[6]. All these components are reported in daily level and available from January 2014 to March 2023, with the exception of 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. This transformation facilitates a consistent and comparable analysis across different metrics. Below is the calculation of market volume index at time t.

$$Market\ Volume\ Index_t = \frac{Market\ Volume_t - Market\ Volume_{min}}{Market\ Volume_{max} - Market\ Volume_{min}} \tag{1}$$

In this paper, we gathered the original data for various components, sourcing some from CoinmarketCap's dataset while obtaining the rest from sources such as Twitter (X), Blockchain explorer, and Google. Following the methodology outlined by Liu and Tsyvinski (2022)[12], we constructed a cryptocurrency market portfolio weighted by market capitalization. Subsequently,

[6] All data is recorded with timestamps in UTC (Coordinated Universal Time).

we calculated the daily values and the 30-day historical volatility of this cryptocurrency market portfolio. To assess the trading activity across exchanges, we utilized the same dataset from CoinmarketCap to compute the daily trading dollar volume.

Additionally, we incorporated daily Google trends data related to the keyword "Cryptocurrency." It is important to note that Google daily trends are presented as relative values. To ensure accurate comparisons spanning from 2014 to 2023, we adjusted these trends data by considering the overall trends value for each respective month. This adjustment allowed us to make meaningful comparisons across the entire period under investigation. Furthermore, in our study, we approximate the daily social media discussions by tracking the number of tweets and posts related to prominent cryptocurrencies such as Bitcoin, Ethereum, and Dogecoin. These cryptocurrencies are frequently discussed on Twitter, making them suitable proxies for gauging social media sentiment. Additionally, we gathered daily data on active wallets from both the Bitcoin and Ethereum blockchains. Specifically, we recorded the number of wallets engaged in cryptocurrency trading activities on each respective date, this on-chain data provides complementary insights to market sentiment, particularly those aspects that might not be readily visible on centralized exchanges. Again, we emphasize all these components are reindexed from 0 to 100. Finally, we compute the overall CryptoSent by weighted value of these components:

$$\begin{aligned} CryptoSent = {} & 0.4 \times Crypto\ Index + 0.25 \times\ Volatility\ Index + 0.2 \times Volume\ Index \\ & + 0.15\ \times\ SocialMedia\&BlockchainAdoption, \end{aligned} \tag{2}$$

where "*SocialMedia&BlockchainAdoption*" is the average index of google index, tweets index and wallet index. We select the weights for the $Crypto\ Index$, $Volatility\ Index$, $Volume\ Index$, and $SocialMedia\&BlockchainAdoption$ according to criteria that better capture major cryptocurrency events, shocks, and crashes in the cryptocurrency market. This is reflected in

Figure 2, Panel B. We conduct a robustness check using an alternative, equal-weighted approach to construct our sentiment index, as detailed in Appendix A. Our results remain consistent.

We next examine the six essential components in our CryptoSent sentiment index and report their trend over time in the following Figure 3.

[Insert Figure 3 Here]

In Figure 3, all six components are reported, each originating at a low level in 2014 when the cryptocurrency market had not yet garnered significant investments. These components exhibited similar upward trends until 2021, where they collectively peaked before gradually cooling down. The initial three components display strikingly similar patterns as they originate from the same dataset. In contrast, the remaining components occasionally capture additional sentiment changes that are not reflected in the data from exchanges. This supplementary data helps enhance the overall sentiment analysis of the entire cryptocurrency market.

To further study the components of CryptoSent and their interactions, we present Table 2, which contains a correlation matrix detailing the relationships among all components.

[Insert Table 2 Here]

The correlations among these components range from 44.59% to 91.83%. Notably, the Crypto Index, Volatility Index, and Volume Index exhibit high correlations, indicating strong interconnections between these aspects of the market. Similarly, the Tweets Index and Wallet Index display significant correlations with other components. However, an exception is observed with the Google Index, showing correlations around 50% with other components. This could be attributed to the occasional lag in Google trends compared to other components, leading to slightly delayed responses in its correlation patterns. Additionally, we present the correlations between the overall CryptoSent and its individual components, all of which remain significantly correlated.

3.2. Sentiment and Expected Cryptocurrency Returns

Even though we strongly believe the cryptocurrency affected by the market sentiment, we need to verify the existence of such effect following the same logic in Section 3. In traditional financial market, Baker and Wurgler (2006)[3] construct a sentiment index using several proxies for investor sentiment measurement, including measures such as trading volume, initial public offering (IPO) activity, closed-end fund discounts, and market-wide returns. However, such tactic is not available in cryptocurrency because of the liquidity.

We then follow the portfolio sort methodology of Ang, Hodrick, Xing, and Zhang (2006). Our goal is to test whether cryptocurrencies with different sensitivities to sentiment (proxied by $\Delta CryptoSent$) have different average returns in the following period. To measure the sensitivity to sentiment, we examine the following regression:

$$r_t^i - r_t^f = \beta_0 + \beta_{CMKT}^i CMKT_t + \beta_{\Delta CryptoSent}^i \Delta CryptoSent_{\mathrm{t}} + \epsilon_t^i \tag{3}$$

where $CMKT_t$ is the market excess return, $\Delta CryptoSent_{\mathrm{t}}$ is the first-order change in our sentiment index, and β_{CMKT}^i and $\beta_{\Delta CryptoSent}^i$ are loadings on cryptocurrency market risk and sentiment risk, respectively.

We analyze the performance of the zero-investment long-short strategy based on the sentiment-related characteristic of $|\beta_{\Delta CryptoSent}|$. Each week, for each cryptocurrency, we use the past 28 days' return to run above regression. We then sort all available cryptocurrencies based on their $|\beta_{\Delta CryptoSent}^i|$'s and group them into 5 quintiles. Then we trace each group's value-weighted excess return of the very next week. And we also construct the long-short strategies, which is constructed by longing group 5 portfolio (includes cryptocurrencies have high sensitivity to sentiment) and shorting group 1 portfolio (includes cryptocurrencies have low sensitivity to sentiment). We find that the result of sentiment-related long-short strategy has statistically significant negative return.

[Insert Table 3 Here]

Table 3 displays the outcomes for portfolios categorized into five quintiles based on their exposure to sentiment, represented as $|\beta_{\Delta CryptoSent}|$. Group 5 comprises cryptocurrencies highly responsive to $\Delta CryptoSent$ in the preceding 28 days, with a notable -2.5% mean return in the subsequent week, demonstrating high significance at the 99% confidence level. In contrast, Group 1 consists of cryptocurrencies exhibiting a neutral response to $\Delta CryptoSent$ during the same period, showing an insignificant mean return of -0.8% in the following week. Groups 2, 3, and 4 follow similar logic and all exhibit insignificant mean returns. Lastly, our long-short sentiment portfolio strategy demonstrates a significant negative return of -1.7% in the immediate subsequent week.

4. Sentiment Risk Factor in the Cross Section of Cryptocurrency Returns

4.1. Sentiment Factor in Explaining Return-based Long Short Strategies

In addition to the sentiment long-short strategy (denoted as **|BETASENT|**) identified in Section 3.2, Liu, Tsyvinski, and Wu (2022)[12] have outlined several other noteworthy long-short strategies in the cryptocurrency market spanning from 2014 to 2020. Indeed, these strategies are categorized based on size, momentum, volume, or volatility. Our findings confirm that these established long-short strategies continue to yield significant returns even when extending the analysis period to March 2023. Table 8 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**). All these long-short strategies are still statistically significant spanning the period from 2014 to 2023.

In the later of this section, we investigate whether we can use factors model to explain these 8 long-short strategies we identify above. The construction of the cryptocurrency market excess returns CMKT is discussed in section 2.2. Then we construct the cryptocurrency sentiment, size and momentum factors following similar method in Fama and French (2015)[9]. Specifically, for sentiment, each week we split the cryptocurrencies into three sentiment groups by $|\beta^{i}_{\Delta CryptoSent}|$: bottom 15% (neutral, N), middle 70% (middle, M), and top 15% (sensitive, S). We then form value-weighted portfolios for each of the three groups. The sentiment factor (CSTM) is the return difference between the portfolios of the sensitive and the neutral portfolios. We construct the momentum factor (CMOM) using three-week momentum and form the momentum factor portfolio based on the intersection of 2 × 3 portfolios. In particular, for each week, we first sort cryptocurrencies into two portfolios based on sentiment exposure $|\beta^{i}_{\Delta CryptoSent}|$. We then form three momentum portfolios within each sentiment portfolio based on past three-week returns. The first, second, and third momentum portfolios are the bottom 15%, middle 70%, and top 15% of the cryptocurrencies based on past three-week returns. The momentum factor is constructed as

$$CMOM = 1/2(Neutral\ High + Sensitive\ High) - 1/2(Neutral\ Low + Sensitive\ Low). \quad (4)$$

Following same methodology, we construct the size factor (CSMB) using market capitalization and form the size factor portfolio based on the intersection of 2 × 3 portfolios. For each week, we first sort cryptocurrencies into two portfolios based on sentiment exposure $|\beta^{i}_{\Delta CryptoSent}|$. We then form three size portfolios within each sentiment portfolio based on market capitalization. The first, second, and third size portfolios are the bottom 15%, middle 70%, and top 15% of the cryptocurrencies based on market capitalization. The Size factor is constructed as

$$CSMB = 1/2(Neutral\ Small + Sensitive\ Small) - 1/2(Neutral\ Big + Sensitive\ Big). \tag{5}$$

Finally, the sentiment factor CSTM is the average return on the six sentiment-sensitive crypto portfolios minus the average return on the six sentiment-neutral crypto portfolios. Specifically,

$$CSTM_{size} = \frac{1}{3}(Sensitive\ Small + Sensitive\ Medium + Sensitive\ Big) - \frac{1}{3}(Neutral\ Small + Neutral\ Medium + Neutral\ Big). \tag{6}$$

$$CSTM_{momentum} = \frac{1}{3}(Sensitive\ Low + Sensitive\ Medium + Sensitive\ High) - \frac{1}{3}(Neutral\ Low + Neutral\ Medium + Neutral\ High) \tag{7}$$

$$CSTM = \frac{1}{2}(CSTM_{Size} + CSTM_{momentum}) \tag{8}$$

We will next examine the returns of long-short portfolios based on strategies related to size, momentum, volume, and volatility, as described above, and report these returns in Table 4.

[Insert Table 4 Here]

With the constructed factors of market, sentiment, size, and momentum. We will consider two-factor, three-factor, and four-factor model of cryptocurrency market to explain the excess return of all eight long-short strategies we identify above. We next add our sentiment factor along with other factors to explain the returns of long-short portfolio strategies.

[Insert Table 5 Here]

Model (1), (2) and (3) of Table 5 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)[12]. Model (5) introduces four-factor model we propose, incorporating CMKT, CSTM, CSMB and CMOM.

Initially, we explored two-factor models, denoted as (1), (2), and (3). Model (1) in Table 5 employed the market factor (CMKT) and the size factor (CSMB). For most strategies, except sentiment and momentum-based ones, the long-short alphas ceased to be significant. All strategies exhibited significant exposures to the cryptocurrency size factor, ranging from 0.019 for sentiment strategies to 0.614 for market capitalization-based strategies. However, due to the insignificant alphas and the low loading of the size factor on sentiment and momentum strategies, this two-factor model failed to adequately explain the sentiment and momentum-based strategies. Subsequently, we explored an alternative two-factor model by combining the cryptocurrency market factor (CMKT) and the cryptocurrency momentum factor (CMOM) in Model (2) of Table 5. This model effectively captured the excess returns of all momentum-related strategies. After incorporating the CMOM factor, the alphas for two and three-week momentum strategies ceased to be statistically significant. These strategies displayed significant exposures to CMOM, with loadings ranging from 0.516 to 0.818. An exception arises in explaining the alpha of the one-week return momentum strategy. One possible explanation is that post-2020, the cryptocurrency market has more popularity, leading to more frequent changes in momentum patterns. And this model struggled to explain the return variation of the sentiment strategy (|BETASENT|) and the size strategy (MCAP). The alphas for these two strategies remained unexplained by Model (2). In Model (3) of Table 5, we examined the regression results of the sentiment factor (CSTM) and the market factor (CMKT). This model effectively explained the excess return of sentiment-related strategies, reducing the alpha of the sentiment strategy to a statistically insignificant -0.4%. Although it couldn't fully capture the alphas of these strategies, all non-momentum strategies displayed significant exposures to the sentiment factor CSTM. In summary, these two-factor models faced limitations in explaining the alphas of all eight long-short strategies. Next, we examined the three-factor model proposed by Liu, Tsyvinski, and Wu (2022) [12] when extending the dataset from 2020 to 2023. Model (4) in Table 5 incorporates the cryptocurrency market, size, and momentum factors. When adjusted for this three-factor model, most of the long-short strategies showed positive results. However, the model failed to capture the alphas of the sentiment strategy and the one- and two-week momentum strategies.

Finally, we propose a four-factor model that combines the CMKT, CSTM, CSMB and CMOM. Model (5) presents results for all eight strategies, compared with three-factor models, the four-factor model can effectively resolve the significant alpha in sentiment strategy, the weekly alpha decreases to insignificant -0.06% from -2% in three-factor model. All non-momentum strategies exposures on CSTM are statistically significant range from 0.147 to 0.662. Non-sentiment strategies have significant loading on CMOM range from 0.102 to 0.819. CSMB is also crucial to explain the alphas for the strategies in size, volume, and volatility. One-week return momentum strategy is the only strategy whose alpha cannot be fully captured by our four-factor model. Recall that Model (2) also struggled to explain the one-week return momentum strategy. It is possible that a similar explanation applies, post-2020, the cryptocurrency market gained more popularity, resulting in more frequent changes in momentum patterns. Compared to previous four models, most of the mean absolute pricing errors are improved especially for sentiment-related strategy.

4.2. Sentiment Factor in Explaining Double-sort Return Portfolio Excess Returns

In the previous Section 4.1, we assessed the explanatory power of our four-factor model. Following the logic of Fama and French (2015)[9], we also exam the 4-factor model regression results for 5×5 Sentiment-Size and 5×5 Sentiment-Momentum portfolios. Specifically, each week, all available cryptocurrencies are allocated to five sentiment groups (Neutral to Sensitive) based on their last 28 days' exposures on sentiment ($|\beta_{\Delta CryptoSent}|$). 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. The 5×5 Sentiment-Momentum portfolios are formed in the same way, except that the second sort variable is past 3-week return momentum. Then we test the four-factor model regression results of all these Sentiment-Size and Sentiment-Momentum strategies.

[Insert Table 6 Here]

Panel A of Table 6 shows intercepts from the from the three-factor regressions for the 5×5 Sentiment-Momentum portfolios. The extreme low momentum cryptocurrency portfolios (left column of the intercept matrix) are not well explained by the three-factor model. Similarly, portfolios comprising cryptocurrencies highly responsive to sentiment (bottom row of the intercept matrix) pose challenges for the three-factor model. For example, consider the portfolio consisting of cryptocurrencies highly responsive to both high momentum and sentiment (bottom right corner of the intercept matrix). Under the three-factor model, its alpha stands at -1.8% per week (t=-1.723). However, in Panel B of Table 6, the introduction of the four-factor regression mitigates these issues. The alpha of the portfolio, consisting of highly momentum-driven and sentiment-responsive cryptocurrencies, rises to a statistically insignificant 0.4% (t=0.656). In comparison with other portfolios having $\beta_{sentiment}$ less than 0.3, this portfolio exhibits significant sentiment exposure, amounting to 1.028 (t=25.6). This implies that the introduced sentiment factor effectively addresses the challenges faced by the portfolio comprising highly momentum-driven and sentiment-responsive cryptocurrencies. Moreover, the alphas of portfolios in the left column and bottom row shrink toward zero, rendering them insignificant or less significant. Besides, our mean of R^2 of four-factor model for 5×5 Sentiment-Momentum portfolios improves 14.8% compared with the mean of R^2 of three-factor model for 5×5 Sentiment-Momentum portfolios. In Panel C of Table 6, we report the sentiment-sensitivity concentration in each momentum quintile portfolios. Specifically, we calculate the value-weight average sentiment-sensitivities in each portfolio, the result shows that sentiment-sensitive cryptos are concentrated in the momentum quintile portfolios with large return or large loss during the past 3 weeks.

[Insert Table 7 Here]

Panel A of Table 7 shows intercepts from the from the three-factor regressions for the 5×5 Sentiment-Size portfolios. Three-factor model effective in explaining the weekly excess return of most portfolios. But the portfolios constructed by big size and sentiment responsive cryptocurrencies (bottom right corner of the intercept matrix) are not well explained by the three-factor model. Under the three-factor model, its alpha stands at -3.1% per week (t=-3.59). After adding sentiment factor to the regression in Panel B of Table 7, the alpha of the portfolio, rises to -1.7% converges to 0 and less significant. In comparison with other portfolios mostly having $\beta_{sentiment}$ less than 0.3, this portfolio exhibits significant sentiment exposure, amounting to 0.661 (t=15.99). This also implies that introduced sentiment mitigate the abnormal excess return from the portfolio comprising big size and sentiment-responsive cryptocurrencies. Also, our mean of R^2 of four-factor model for 5×5 Sentiment-Momentum portfolios improves 10.7% compared with the mean of R^2 of three-factor model for 5×5 Sentiment-Momentum portfolios. In Panel C of Table 7, we report the sentiment-sensitivity concentration in each size quintile portfolios. Specifically, we calculate the value-weight average sentiment-sensitivities in each portfolio, the result shows that sentiment-sensitive cryptos are concentrated in the size quintile portfolios with small market capitalization.

In summary, the introduction of the sentiment factor CSTM proves effective in either resolving or mitigating the substantial alphas observed in portfolios with highly momentum-driven, sentiment-responsive, or large-sized cryptocurrencies.

We further investigate the sentiment sensitive cryptocurrencies' concentration in different quintile portfolios in the following Table 10.

[Insert Table 10 Here]

The result in Table 10 shows that sentiment sensitive cryptocurrencies are mainly existed in the portfolios with large loss or large return in the past 3 weeks. It also shows that sentiment sensitive cryptocurrencies are relatively mainly located in the portfolios with small size. Such variation within quintile groups also explains the improvement of our four-factor model compared with previous three-factor model.

4.3. Fama-MacBeth (1973)[7] Regression Analysis

We assess the robustness of our cross-sectional regression findings employing the Fama-MacBeth method. Initially, we categorize each cryptocurrency into one of five portfolios based on their respective characteristics. These characteristics include $|\beta_{\Delta CryptoSent}|$, MCAP, and R3,0, introduced earlier. The final characteristic, β_{CMKT}, represents the market risk exposure of each cryptocurrency and is computed using the cryptocurrency CAPM model. Subsequently, we utilize the portfolio rank number as the explanatory variable.

[Insert Table 8 Here]

Panel A of Table 8 presents the results of Fama-MacBeth regression focusing on individual characteristics. Models (1) to (3) all show statistically significant slopes, indicating that these specific factors possess explanatory power in the cross-sectional cryptocurrency market. In Panel B, models (4) to (6) represent two-characteristic regressions after incorporating β_{CMKT}. The outcomes closely resemble those in Panel A. $|\boldsymbol{\beta}_{\boldsymbol{\Delta CryptoSent}}|$, MCAP, and R3,0 still exhibit significant slopes. Moving to Panel C, models (7) to (11) explore more comprehensive Fama-Macbeth regressions involving more than three characteristics. All slopes corresponding to $|\boldsymbol{\beta}_{\boldsymbol{\Delta CryptoSent}}|$ are statistically significant, with t-statistics lower than -5.65, underscoring the importance of the sentiment factor in explaining cross-sectional returns. An interesting observation is that the slopes of β_{CMKT} in all models lack significance. This contrasts with our previous findings using value-weighted portfolio strategies. One potential explanation for this difference lies in the Fama-MacBeth regression treating each observation equally, akin to equally weighted portfolios, which might account for the variance in results. More specifically, model (10) is the three-factor model of Liu and Tsyvinski (2022)[12], there exists significant alpha in Fama-Macbeth regression. As comparison, model (11) is our four-factor model, after adding the sentiment factor, our model can explain the cross-sectional variation with insignificant alpha (-0.003). In summary, the sentiment factor plays a significant role in the Fama-MacBeth weekly cross-sectional regression.

4.4. PCA Analysis of Cryptocurrency Returns

In this section, we conduct principal component analysis on the eight significant long-short strategies we discussed. We test whether a small number of principal components can capture the variation of the strategies' returns. We show that four components explain most of variation in these strategies' returns. We test the correlations between the four principal components and the four cryptocurrency factors.

[Insert Table 9 Here]

Table 9 presents results of the principal component analysis for the eight long-short strategies. Panel A of Table 9 reports the proportion of variance explained. The first 4 principal components explain 30%, 24%, 11% and 11% respectively. The first four components explain more than 75% of the variation in the eight long-short strategies. Panel B of Table 9 reports the correlation matrix of the first four principal components and the four cryptocurrency factors in our model. The first principal component positively correlates with the cryptocurrency momentum factor with 50.54% correlation. The second principal component has significant exposure (36.36%) to the cryptocurrency size factor. The third principal component has strong positive correlation (52.36%) with cryptocurrency sentiment factor. The fourth principal component has strong negative correlation with market factor (-21.30%) and sentiment factor (-49.97%) respectively. In summary, most of the variation of eight long-short strategies can be explained by the four principal components, and the principal component analysis result is consistent with our four factors.

4.5. Strategies Conditional on Sentiment Index

Another important application of our sentiment index is that it can be a signal of some specific long trading strategies. Stambaugh, Yu, and Yuan (2012)[17] find the short leg of long-short strategies are more likely to be affected by the market sentiment. Baker and Wurgler (2006)[3] find that when beginning-of-period proxies for sentiment are low, subsequent returns are relatively high for small stocks, young stocks, high volatility stocks, un- profitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. When sentiment is high, on the other hand, these categories of stock earn relatively low subsequent returns. With the sentiment index we constructed in this paper, we can also test the sentiment conditional return of different cryptocurrencies grouped by different characteristics.

[Insert Figure 3 Here]

Figure 3 describes the sentiment conditional return of different cryptocurrencies group by the characteristics we discussed. For instance, the first sub-figure illustrates the difference of cryptocurrency portfolios sorted by the MCAP, at the beginning of each week, cryptocurrencies are sorted into 10 groups based on its MCAP. If the $\Delta CryptoSent$ at the beginning of that week is higher than the median of $\Delta CryptoSent$, we classify the incoming week as “high sentiment week” otherwise it is classified as “low sentiment week”. We monitor the performance of these portfolios over the subsequent week and compute the conditional return based on sentiment for each portfolio. The blue bar plots the average return of the portfolio when there is high sentiment at the start of the week, whereas the orange bar plots the average return of the portfolio under low sentiment conditions. The blue line indicates the disparity in mean returns between high and low sentiment conditions. Notably, non-momentum portfolios exhibit a substantial difference in returns between group 1 and group 10, while momentum-related portfolios display a considerable difference primarily in group 10. These findings affirm the influence of sentiment on the returns of these strategies in the cryptocurrency market.

5. Conclusion

Given the escalating significance of investor sentiment in financial market investing, coupled with the rapid evolution of blockchain and cryptocurrency sectors, it becomes imperative to delve deeply into the interplay between investor sentiment and cryptocurrency returns. In this paper, we explore sentiment as a pivotal factor in explaining 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.

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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	54.50	0.50	619.10	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	29.30
2020	2384	238.19	2.57	83654.86	59.49
2021	2981	981.87	7.50	158966.40	244.39
2022	2702	668.00	4.65	288551.00	174.35
2023	2096	541.60	4.32	50796.58	159.72

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.

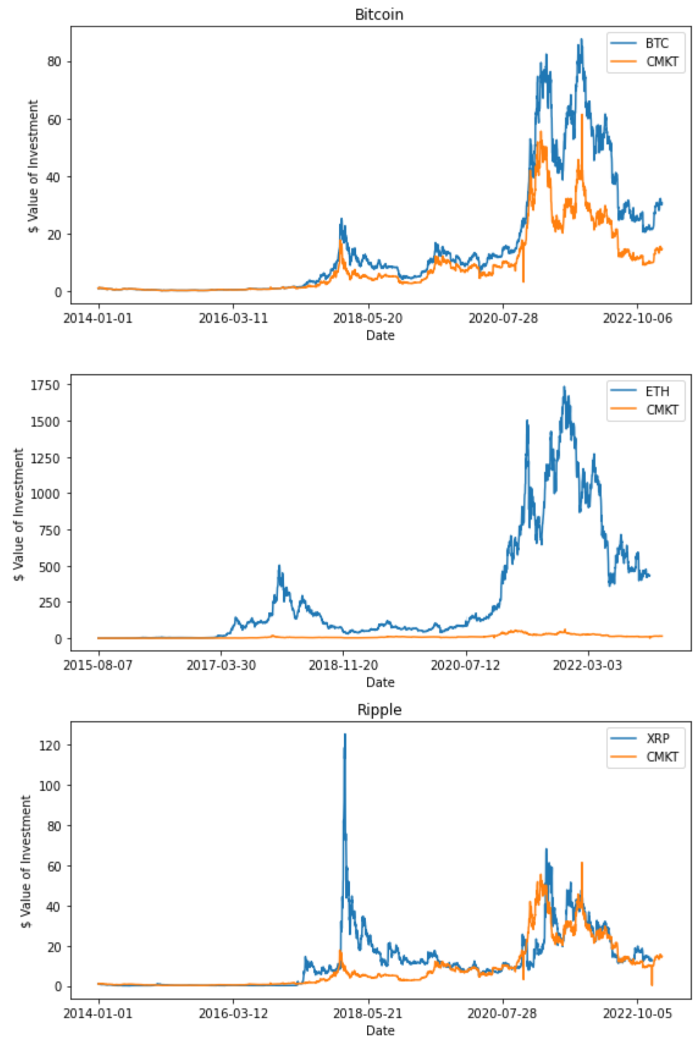
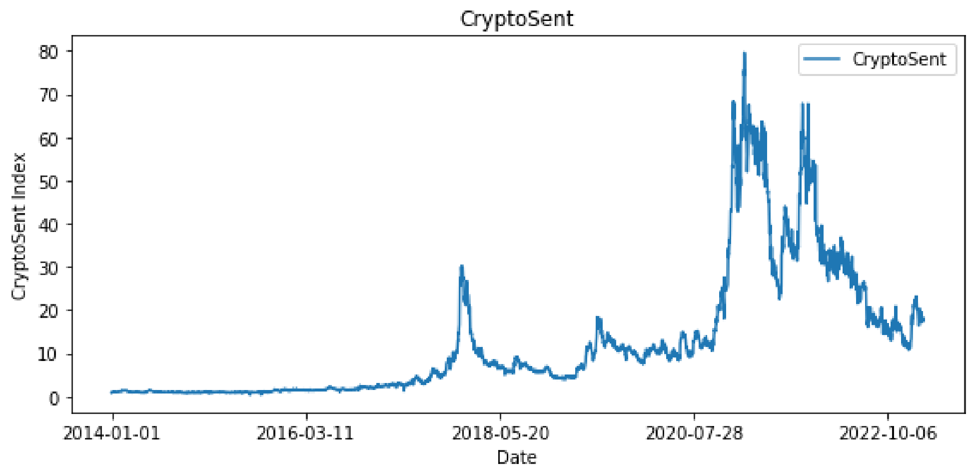


Figure 2. Cryptocurrency Sentiment Index CryptoSent Time Series Plot

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: CryptoSent Time Series Trend



Panel B: CryptoSent Time Series Trend with Important Events

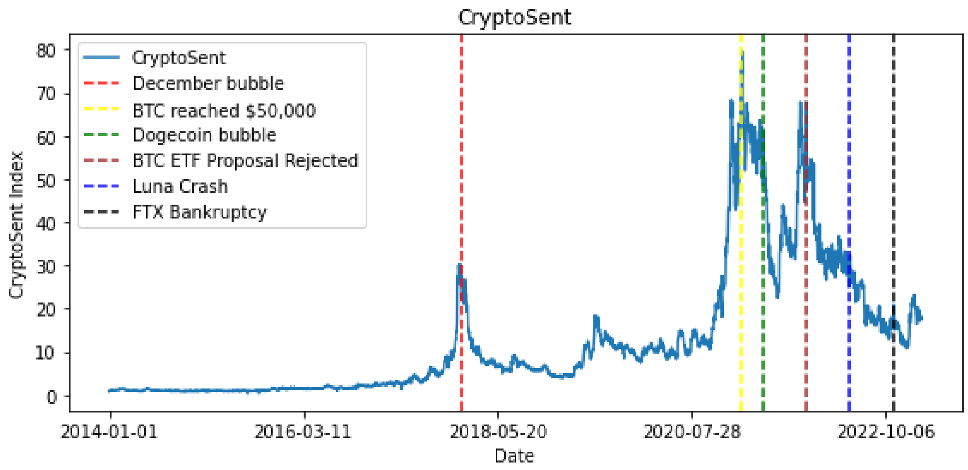


Figure 3. Cryptocurrency Sentiment Index CryptoSent Components

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.

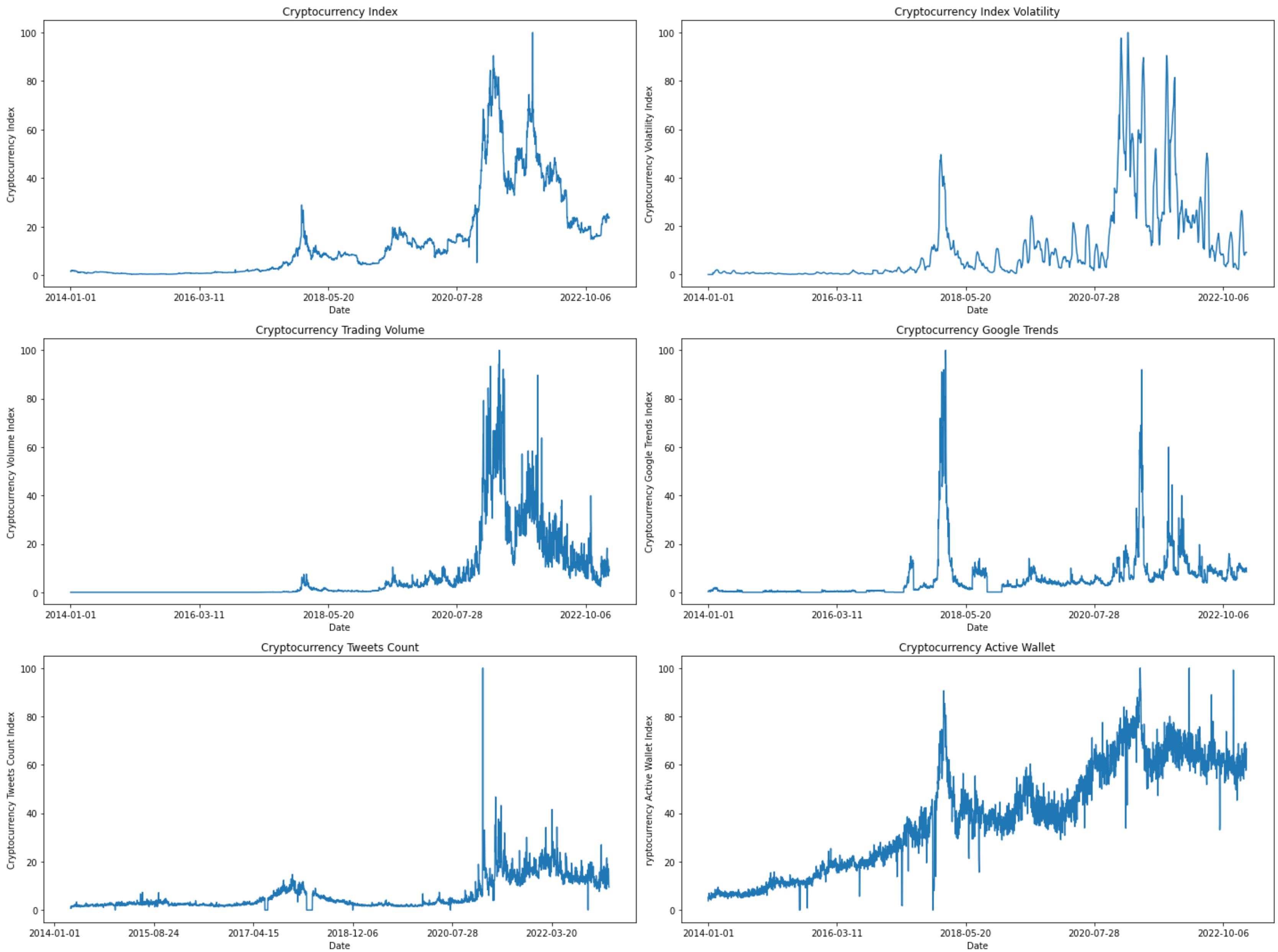

Cryptocurrency Index
Cryptocurrency Index
Date
Cryptocurrency Index Volatility
Cryptocurrency Volatility Index
Date
Cryptocurrency Trading Volume
Cryptocurrency Volume Index
Date
Cryptocurrency Google Trends
Cryptocurrency Google Trends Index
Date
Cryptocurrency Tweets Count
Cryptocurrency Tweets Count Index
Date
Cryptocurrency Active Wallet
ryptocurrency Active Wallet Index
Date
2014-01-01
2016-03-11
2018-05-20
2020-07-28
2022-10-06
2015-08-24
2017-04-15
2018-12-06
2022-03-20

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	-0.030
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	0.020	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	0.030	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
|BETASENT|	(1)	-0.018***	(-2.88)	0.094**	(2.01)	-0.019***	(-0.48)					0.009	0.090
	(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	0.090
	(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)	-0.110***	(-2.96)			0.358	0.070
	(5)	-0.009	(-1.52)	0.055	(1.20)	-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)	-0.100	(-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

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***	(16.40)			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	0.130
	(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)	0.100	0.125
STDPRCVOL	(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 ($|\beta_{\Delta CryptoSent}|$). 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 **($|\boldsymbol{\beta_{\Delta CryptoSent}}|$)** 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 $\boldsymbol{R(t) - R_f(t) = \alpha + \beta_{cmkt}\, CMKT + \beta_{size}\, CSMB + \beta_{momentum}\, CMOM + e(t)}$										
Sentiment ↓			a					$t(a)$		
Neutral	-0.020	-0.009	-0.003	0.008	0.005	-3.171	-1.587	-0.704	1.359	0.370
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	0.010	-2.045	-1.554	0.248	-0.463	1.168
4	-0.008	0.014	-0.005	0.004	0.006	-1.062	0.770	-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	0.260
2	0.316	0.369	0.436	0.239	0.223	0.178	0.126	0.113	0.203	0.210
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	0.280	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	0.160	0.172	0.215
Panel B: Four-factor model regression: $\boldsymbol{R(t) - R_f(t) = \alpha + \beta_{cmkt}\, CMKT + \beta_{sentiment}\, CSTM + \beta_{size}\, CSMB + \beta_{momentum}\, CMOM + e(t)}$										
Sentiment ↓			a					$t(a)$		
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	0.020	-0.001	0.007	0.010	-0.666	1.045	-0.221	0.900	1.173
Sensitive	-0.005	0.010	-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	0.630	0.663	0.708	13.558	13.686	19.072	15.701	7.608
2	0.690	0.700	0.740	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	14.810	13.654	12.693	13.640	10.480

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	13.710
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	0.240
2	0.176	0.113	0.090	0.053	0.149	3.444	3.089	2.779	0.901	2.465
3	0.264	0.290	0.096	0.118	0.118	6.540	7.431	2.025	2.843	2.216
4	0.141	0.235	0.159	0.124	0.191	2.980	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	0.090	0.040	0.030	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	2.440	2.400	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	-2.830
Sensitive	-0.003	0.166	0.150	0.099	0.074	-0.058	2.352	2.917	1.926	1.769
Sentiment ↓			$\beta_{momentum}$					$t(\beta_{momentum})$		
Neutral	-0.270	-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	-6.120	-2.611	-1.825	1.729	4.384
3	-0.290	-0.150	-0.056	0.035	0.346	-7.262	-3.851	-1.200	0.856	6.569
4	-0.261	-0.167	-0.066	-0.006	0.301	-5.552	-1.510	-1.805	-0.134	5.929
Sensitive	-0.287	-0.118	0.007	0.029	0.220	-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	0.260
2	0.333	0.382	0.446	0.240	0.233	0.176	0.125	0.112	0.203	0.209
3	0.439	0.381	0.279	0.310	0.257	0.139	0.135	0.162	0.143	0.183
4	0.270	0.088	0.360	0.290	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 ($|\beta_{\Delta CryptoSent}|$)

	Quintile				
	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 ($|\beta_{\Delta CryptoSent}|$). 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 quantile portfolios' average exposure on sentiment **($|\boldsymbol{\beta_{\Delta CryptoSent}}|$)** weighted by market capitalization.

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

Size →	Small	2	3	4	Big	Small	2	3	4	Big
Panel A: Three-factor intercepts: CMKT, CSMB, CMOM										
Sentiment ↓			a					$t(a)$		
Neutral	0.126	-0.009	0.001	-0.005	-0.001	0.649	-1.316	0.119	-0.604	-0.327
2	-0.010	0.008	-0.009	0.001	0.008	-0.759	0.865	-1.343	0.191	1.017
3	-0.001	0.000	0.001	-0.005	0.001	-0.133	0.051	0.075	-0.890	0.122
4	0.005	0.009	0.000	-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	0.550	4.005	0.137	0.125	0.182	0.074
2	0.346	0.249	0.323	0.330	0.277	0.281	0.192	0.144	0.136	0.157
3	0.409	0.390	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:

$$\boldsymbol{R(t) - R_f(t) = \alpha + \beta_{cmkt}\, CMKT + \beta_{sentiment}\, CSTM + \beta_{size}\, CSMB + \beta_{momentum}\, CMOM + e(t)}$$

Sentiment ↓			a					$t(a)$		
Neutral	0.134	-0.005	0.002	-0.004	-0.002	0.683	-0.819	0.377	-0.412	-0.499
2	-0.006	0.010	-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	0.650	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	0.670	0.673	10.009	9.886	10.210	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	2.180	2.647	0.567
3	0.135	0.046	0.065	0.150	0.147	2.563	1.175	1.330	4.352	3.741
4	0.152	0.113	0.166	0.155	0.173	3.467	2.029	2.480	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	7.570	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	0.000	14.015	7.688	4.934	4.110	0.004
4	0.490	0.419	0.270	0.258	-0.209	10.816	7.281	3.910	6.373	-4.420
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	0.060	-0.030	1.415	1.887	1.719	1.146	-1.416
2	-0.053	-0.013	0.040	0.040	-0.015	-0.646	-0.243	0.966	1.039	-0.330
3	0.007	0.055	0.161	0.008	0.029	0.141	1.420	3.340	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	0.330	3.398	1.224	1.765	-0.306

Sentiment ↓	R^2					$S(e)$				
Neutral	0.007	0.362	0.344	0.210	0.552	4.009	0.135	0.125	0.182	0.074
2	0.355	0.255	0.330	0.340	0.278	0.279	0.191	0.143	0.135	0.157
3	0.417	0.392	0.311	0.374	0.346	0.180	0.136	0.167	0.119	0.135
4	0.422	0.240	0.165	0.388	0.322	0.151	0.192	0.230	0.135	0.157
Sensitive	0.339	0.278	0.263	0.320	0.525	0.193	0.173	0.197	0.183	0.139

Panel C. Size Quintiles' Weighted Average Exposures on Sentiment ($|\beta_{\Delta CryptoSent}|$)

	Quintile				
	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 ($\boldsymbol{\beta_{CMKT}}$), sentiment beta ($|\boldsymbol{\beta_{\Delta CryptoSent}}|$**)**, market capitalization (**MCAP**), last-day price (**PRC**), and three-week (**R 3,0**) return.

Panel A: One-Factor Model

Model	Intercept	β_{CMKT}	$\|\beta_{\Delta CryptoSent}\|$	MCAP	R 3,0	$\overline{R^2}$
	0.012		-0.005			
(1)	(2.16)		(-5.80)			1.55%
	0.053			-0.009		
(2)	(2.09)			(-1.59)		1.58%
	-0.007				0.002	
(3)	(-1.17)				(1.75)	2.31%

Panel B: Two-Factor Model

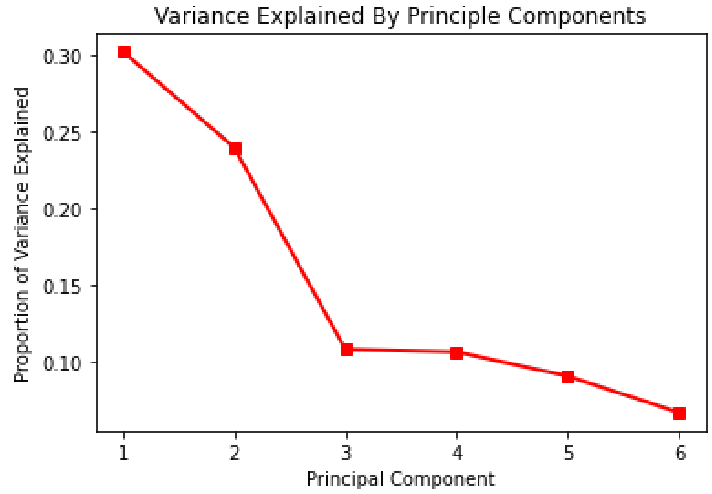
Model	Intercept	β_{CMKT}	$\|\beta_{\Delta CryptoSent}\|$	MCAP	R 3,0	$\overline{R^2}$
	0.015	-0.001	-0.005			
(4)	(2.76)	(-0.89)	(-6.05)			3.12%
	0.038	0.003		-0.007		
(5)	(2.11)	(0.801)		(-1.48)		3.09%
	-0.005	-0.001			0.002	
(6)	(-0.81)	(-0.84)			(1.69)	3.82%

Panel C: Multiple-Factor Model						
Model	**Intercept**	β_{CMKT}	$\lvert\beta_{\Delta CryptoSent}\rvert$	**MCAP**	**R 3,0**	$\overline{R\text{^}2}$
	-0.000	-0.001	-0.005	0.003		
(7)	(-0.016)	(-0.64)	(-5.66)	(1.48)		4.79%
	0.007	-0.001	-0.005		0.002	
(8)	(1.13)	(-0.97)	(-6.33)		(2.07)	5.38%
	-0.009		-0.005	0.003	0.002	
(9)	(-0.72)		(-5.65)	(1.49)	(1.85)	5.46%
	-0.026	-0.001		0.005	0.002	
(10)	(-2.05)	(-0.50)		(2.25)	(1.31)	5.51%
	-0.003	-0.001	-0.005	0.003	0.002	
(11)	(-0.21)	(-0.82)	(-6.02)	(1.17)	(1.21)	7.02%

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

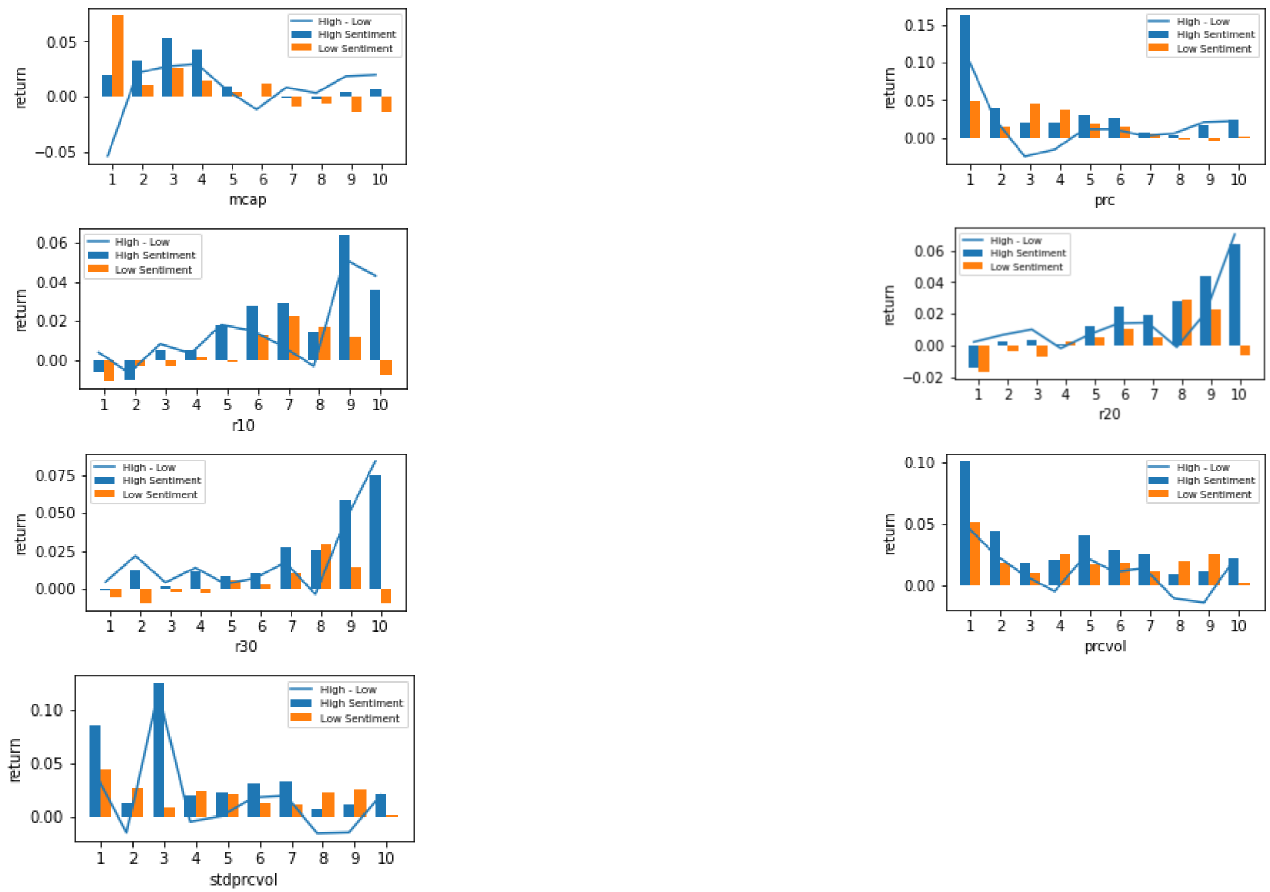


Panel B. Correlation

	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 3. Long Short Portfolio Strategy Conditional on Long-Short Leg

Figure 3 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 *SocialMedia&BlockchainAdoption*. We next report our portfolio sort results in the following Table A1.

Table A1 Portfolios Sorted by Exposure to Equal-weighted 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 A. Sentiment Strategy Weekly Excess Return						
	Quintiles					
	1	**2**	**3**	**4**	**5**	**5-1**
$\left\|\beta^{i}_{\Delta CryptoSent}\right\|$	**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 A1, 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.