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.

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 four 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's daily snapshots, where cryptocurrency data has been available since 2013. Our dataset covers the period from January 2014 to February 2023. CoinMarketCap is a website that offers market capitalization, price, volume, and additional data for thousands of cryptocurrencies. Launched in 2013, it has become one of the leading platforms for cryptocurrency market data, providing real-time information on prices, trading volumes, and market capitalizations of cryptocurrencies across various exchanges.

For each cryptocurrency listed on the website, its price is calculated by taking the volume-weighted average of all prices reported for each market. To be listed, a cryptocurrency must meet specific criteria, such as being traded on a public exchange with an API that reports the last traded price and the last 24-hour trading volume. Moreover, it must have nonzero trading volume on at least one supported exchange to ensure 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]. We present summary statistics in the following Table 1.

[Insert Table 1 Here]

The number of coins in our sample increases 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 one-month Treasury bill rate. We present a time-series graph that tracks the performance of the CMKT and three major cryptocurrencies in the market: Bitcoin, Ripple, and Ethereum (noting that Ethereum was introduced in 2015). To facilitate comparison, the values are reported in terms of the U.S. dollar value of an initial one-dollar investment from the inception of each cryptocurrency.

[Insert Figure 1 Here]

Figure 1 illustrates the cumulative dollar wealth generated from 1-dollar investments in the cryptocurrency market index, Bitcoin, Ripple, and Ethereum. Bitcoin saw a return exceeding 80-fold in 2021, showing a high correlation with the cryptocurrency market index.

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

Ripple peaked at the beginning of 2018, while Ethereum generated the most significant abnormal returns in 2021, largely attributed to the rising popularity of Web 3.0 technologies.

3 Sentiment Index Construction and Expected Cryptocurrency Returns

In this section, we outline the methodology employed to develop our cryptocurrency sentiment index. Additionally, we present evidence demonstrating the index's substantial predictive ability regarding the expected returns of cryptocurrencies in the following week and subsequent month.

3.1 Sentiment Index Construction

Investor sentiment is a crucial element in finance, significantly influencing financial markets and investment decisions. It encompasses the collective mood, emotions, and attitudes of investors and market participants toward specific financial assets, markets, or the broader economy. This sentiment is a key driver of market volatility. In periods of positive sentiment, optimism prevails among investors, leading to heightened buying activity and rising prices. On the flip side, negative sentiment, characterized by fear and pessimism, triggers selling pressure, resulting in price declines. The volatility spurred by these sentiment shifts offers both risks and opportunities to investors.

Makarov and Schoar (2021), Canayaz, Cao, Nguyen, and Wang (2023), Philippas, Rjiba, Guesmi, and Goutte (2019), as well as Liu and Tsyvinski (2021) 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 starts at a low level in 2014 when the cryptocurrency market had not yet garnered significant investments. It exhibits upward trends until 2021, reaching a peak before starting to decline gradually. The index effectively captures several major shocks to the cryptocurrency market. For instance, on December 17, 2017, Bitcoin hit a new all-time high of $19,783, only to fall by 45% from its peak within a week. On February 16, 2021, Bitcoin reached $50,000 for the first time. Prior to May 19, 2021, the market was buoyant, fueled by positive developments such as Coinbase going public on NASDAQ and the surging popularity of meme tokens, with Dogecoin's value skyrocketing by 20,000% within a year. On May 19, the 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. 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 example for calculation of market volume index at time t.

$$Market\ Volume\ Index_t = \frac{\text{Market Volume}_t - \text{Market Volume}_{min}}{\text{Market Volume}_{max} - \text{Market Volume}_{min}} \tag{1}$$

In this paper, we gather 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), we construct a cryptocurrency market portfolio weighted by market capitalization. Subsequently, we calculate the daily values and the 30-day historical volatility of this cryptocurrency market portfolio. To assess the trading activity across exchanges, we utilize the same dataset from CoinmarketCap to compute the daily trading dollar volume.

Additionally, we incorporate 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 adjust 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 gather daily data on active wallets from both the Bitcoin and Ethereum blockchains. Specifically, we record 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:

$$\begin{aligned} CryptoSent =& 0.4 \times Crypto\ Index + 0.25 \times Volatility\ Index + 0.2 \times Volume\ Index \\ & + 0.15 \times Social\ Media\&Blockchain\ Adoption, \end{aligned} \tag{2}$$

where “Social Medi&Blockchain Adoption” 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 exhibit similar upward trends until 2021, where they collectively peak 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 the following 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

While it may seem apparent that cryptocurrencies are influenced by market sentiment, this section rigorously tests that hypothesis. In the traditional financial market, Baker and Wurgler (2006) construct a sentiment index using a variety of proxies to measure investor sentiment, such as trading volume, initial public offering (IPO) activity, closed-end fund discounts, and market-wide returns. However, this approach is not directly applicable to the cryptocurrency market due to issues related to liquidity.

We 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:

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

where $CMKT_t$ is the market excess return, $\Delta CryptoSent_t$ 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 $|\beta_{\Delta CryptoSent}^i|$. To do this, we compute the past 28 days' return for each cryptocurrency and proceed to run the regression. Subsequently, cryptocurrencies are ranked based on their $|\beta_{\Delta CryptoSent}^i|$ values and divided into five quintiles. Then we trace each group's value-weighted excess return of the very next week. Moreover, we implement long-short strategies by taking long positions in the fifth quintile portfolio, which includes cryptocurrencies with high sensitivity to sentiment, and short positions in the first quintile portfolio, containing cryptocurrencies with low sentiment sensitivity. Our findings reveal that the sentiment-related long-short strategy yields a 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 $|\beta_{\Delta CryptoSent}^i|$. Group 5 consists of cryptocurrencies that have shown a high sensitivity to sentiment (proxied by $\Delta CryptoSent$) 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

In this section, we develop the cryptocurrency sentiment factor and subsequently demonstrate its predictive power in explaining the returns of portfolio strategies. Additionally, we illustrate its significance as a priced common risk factor across 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 $|\beta_{SENT}|$) identified in Section 3.2, Liu, Tsyvinski, and Wu (2022) have identified several other long-short strategies in the cryptocurrency market, spanning from 2014 to 2020. These strategies are distinguished based on factors such as size, momentum, volume, and volatility. Our analysis, extended to March 2023, corroborates that these well-established long-short strategies continue to generate significant returns, affirming their validity and effectiveness over a broader temporal scope.

In this section, we elaborate on the construction of eight long-short strategies, mirroring the approach taken by Liu, Tsyvinski, and Wu (2022). The construction of the cryptocurrency market excess returns (CMKT) is described previously in Section 2.2. Following a methodology akin to that of Fama and French (2015), we proceed to construct factors for cryptocurrency sentiment, size, and momentum. Specifically for sentiment, we categorize cryptocurrencies weekly into three groups based on the absolute value of their sentiment beta $|\beta^i_{\Delta CryptoSent}|$: the bottom 15% (labeled "neutral", N), the middle 70% ("middle", M), and the top 15% ("sensitive", S). Value-weighted portfolios are then formed for each group. The sentiment factor (CSTM) is derived from the return difference between the "sensitive" and "neutral" portfolios. For the momentum factor (CMOM), we adopt a three-week momentum approach, organizing cryptocurrencies into 2 $\times$ 3 portfolios based on their sentiment exposure and past three-week returns. Specifically, cryptocurrencies are initially sorted into two groups according to their sentiment exposure $|\beta^i_{\Delta CryptoSent}|$. Within each sentiment group, we then classify cryptocurrencies into three momentum portfolios—bottom 15%, middle 70%, and top 15%—based on their performance over the past three weeks. The momentum factor is constructed as

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

Following same methodology, we construct the size factor (CSMB) using market capitalization and form the size factor portfolio based on the intersection of 2 $\times$ 3 portfolios. For each week, we first sort cryptocurrencies into two portfolios based on sentiment exposure $|\beta^i_{\Delta CryptoSent}|$. Subsequently, within each sentiment-based grouping, cryptocurrencies are further divided into three size-based portfolios determined by their market capitalization: the bottom 15% ("small", S), the middle 70% ("medium", M), and the top 15% ("big", B). These classifications allow us to observe the impact of size in conjunction with sentiment on cryptocurrency returns. The Size factor is constructed as

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

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,

$$\begin{aligned} CSTM_{size} = &\frac{1}{3}(Sensitive\ Small + Sensitive\ Medium + Sensitive\ Big) - \\ &\frac{1}{3}(Neutral\ Small + Neutral\ Medium + Neutral\ Big). \end{aligned} \quad (6)$$

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

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

With the factors of market, sentiment, size, and momentum now constructed, we now present the performance of long-short portfolios, crafted based on size, momentum, volume, and volatility strategies as previously described, in Table 4.

[Insert Table 4 Here]

Table 4 provides statistics for size, momentum, volume, and volatility-related strategies spanning the period from 2014 to 2023. Panel A details the mean returns of quintile portfolios based on market capitalization (MCAP) and the last-day price (PRC). Panel B illustrates the mean returns of quintile portfolios derived from one-week (R 1,0), two-week (R 2,0), and three-week (R 3,0) return measures. Panel C provides insights into the mean returns of quintile portfolios according to the price volume (PRCVOL) measure. Finally, Panel D offers data on the mean returns of quintile portfolios calculated based on the standard deviation of price volume (STDPRCVOL). The results confirm that these long-short strategies remain statistically significant throughout the observed period from 2014 to 2023.

We next employ two-factor, three-factor, and four-factor models to explain the excess returns of the eight long-short strategies identified earlier. Subsequently, we will integrate our sentiment factor alongside the other established factors to further elucidate the returns of these 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). Model (5) introduces four-factor model we propose, incorporating CMKT, CSTM, CSMB and CMOM.

Initially, we assess two-factor models, labeled as (1), (2), and (3), to understand their efficacy in explaining various long-short strategy returns. Model (1), presented in Table 5, combined the market factor (CMKT) and the size factor (CSMB). This model finds limited success; it fails to maintain significant alphas for sentiment and momentum-based strategies, despite revealing substantial exposure to the size factor across most strategies. Particularly, exposure to CSMB ranges from -0.019 in sentiment strategies to -0.614 in market capitalization-based strategies. The inadequacy of this model is especially apparent in explaining sentiment and momentum-based strategies due to the low size factor loading and insignificant alphas.

Subsequently, we explore 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 captures the excess returns of all momentum-related strategies. After incorporating the CMOM factor, the alphas for two and three-week momentum strategies cease 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 struggles to explain the return variation of the sentiment strategy ($|\beta_{SENT}|$) and the size strategy (MCAP). The alphas for these two strategies remain unexplained by Model (2).

In Model (3) of Table 5, the sentiment factor (CSTM) and the market factor (CMKT) significantly address the excess returns of sentiment-related strategies, reducing their alphas to insignificant values. While this model shows some limitations in fully capturing strategy alphas, it confirms substantial exposure to the sentiment factor CSTM for all non-momentum strategies.

Upon reviewing these two-factor models, it becomes evident that they could not comprehensively explain the alphas for all eight long-short strategies. Thus, we proceed to evaluate the three-factor model proposed by Liu, Tsyvinski, and Wu (2022), extending our dataset to include 2020 to 2023. Model (4) in Table 5, which incorporates market, size, and momentum factors, demonstrated improved explanatory power for most long-short strategies. Nonetheless, it falls short of explaining the alphas for the sentiment strategy and the one- and two-week momentum strategies.

Crucially, we introduce a four-factor model that integrates the CMKT, CSTM, CSMB, and CMOM factors. Model (5) offers insights across all eight strategies and demonstrates a notable improvement over the three-factor models, particularly in addressing the significant alpha associated with the sentiment strategy. This alpha diminishes from -2% to an insignificant -0.06%. The model reveals that exposures to CSTM for all non-momentum strategies are statistically significant, ranging from 0.147 to 0.662, indicating a pronounced impact of sentiment on these strategies. Moreover, non-sentiment strategies exhibit significant loadings on CMOM, varying between 0.102 and 0.819, while CSMB is essential for explaining the alphas of strategies focused on size, volume, and volatility. The exception within this model is the one-week return momentum strategy, whose alpha cannot be fully explained by our four factor model, mirroring the challenges faced by Model (2). This persistence might be attributed to the cryptocurrency market's increased dynamism post-2020, characterized by more rapid shifts in momentum patterns. Relative to the preceding models, the four-factor model significantly reduces mean absolute pricing errors, particularly enhancing the accuracy of sentiment-related strategy predictions.

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

In the previous Section 4.1, we evaluated the explanatory power of our four-factor model. Following the methodology of Fama and French (2015), we extend our analysis to examine the four-factor model's regression results for both 5 × 5 Sentiment-Size and 5 × 5 Sentiment-Momentum portfolios. Specifically, each week, we categorize all available cryptocurrencies into five sentiment groups, ranging from Neutral to Sensitive, based on their sentiment exposure over the last 28 days ($|\beta^i_{\Delta CryptoSent}|$). Cryptocurrencies are also separately sorted into five size groups, from Small to Big, according to their market capitalizations. The combination of these two sorting criteria results in the formation of 25 value-weighted Sentiment-Size portfolios. Similarly, we create 5 $\times$ 5 Sentiment-Momentum portfolios, employing the same sentiment grouping, but the second sort is based on the past three-week return momentum. Subsequently, we apply the four-factor model to regress the returns of these Sentiment-Size and Sentiment-Momentum strategies, testing the model's robustness in explaining variations across these diversified portfolios.

[Insert Table 6 Here]

Panel A of Table 6 displays intercepts from the three-factor regressions for the 5 $\times$ 5 Sentiment-Momentum portfolios. The extreme low momentum cryptocurrency portfolios (left column of the intercept matrix) are not adequately explained by the three-factor model. Similarly, portfolios containing cryptocurrencies highly sensitive to sentiment (bottom row of the intercept matrix) also present challenges for this model. For instance, the portfolio that is highly sensitive to both high momentum and sentiment (located in the bottom right corner of the intercept matrix) exhibits an alpha of -1.8% per week ($t = -1.723$) under the three-factor framework.

However, Panel B of Table 6 demonstrates how the introduction of the four-factor regression addresses these challenges. The alpha of the portfolio, consisting of highly momentum-driven and sentiment-sensitive 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-sensitive cryptocurrencies. Additionally, the alphas for portfolios in both the left column and bottom row tend toward zero, becoming insignificant or less significant. Furthermore, the average R^2 of the four-factor model for the

5 × 5 Sentiment-Momentum portfolios shows a 14.8% improvement over the three-factor model.

In Panel C of Table 6, we report the sentiment-sensitivity concentration in each momentum quintile portfolios. By calculating the value-weighted average sentiment sensitivities in each portfolio, we observe that sentiment-sensitive cryptocurrencies are predominantly found in quintile portfolios that experienced significant returns or losses over the past three weeks.

[Insert Table 7 Here]

Similar to Table 6, Panel A of Table 7 displays intercepts from the three-factor regressions for the 5 × 5 Sentiment-Size portfolios. The three-factor model is effective in explaining the weekly excess returns for most portfolios. However, portfolios constructed from cryptocurrencies that are both large in size and highly sensitive to sentiment (located in the bottom right corner of the intercept matrix) are not well-explained by the three-factor model. Under this model, the alpha for such a portfolio stands at -3.1% per week ($t = -3.59$).

Upon introducing the sentiment factor into the regression, as shown in Panel B of Table 7, the alpha of the portfolio improves to -1.7%, becoming closer to zero and less significant. Compared to other portfolios, predominantly with $\beta_{sentiment}$ less than 0.3, this portfolio demonstrates significant sentiment exposure at 0.661 ($t = 15.99$). This suggests that the addition of the sentiment factor helps to mitigate the abnormal excess returns from portfolios consisting of large-size and sentiment-sensitive cryptocurrencies. Additionally, the average R^2 of the four-factor model for the 5 × 5 Sentiment-Size portfolios shows a 10.7% improvement over the three-factor model.

In Panel C of Table 7, we detail the concentration of sentiment sensitivity within each size quintile portfolio. By calculating the value-weighted average sentiment sensitivities for each portfolio, we find that sentiment-sensitive cryptocurrencies are predominantly concentrated in quintile portfolios with smaller market capitalizations.

In summary, the incorporation of the sentiment factor (CSTM) into our analysis has been instrumental in addressing, if not entirely resolving, the significant alphas associated with portfolios characterized by high momentum, strong sentiment sensitivity, or large size in cryptocurrencies. This underscores the critical role of sentiment in the dynamics of cryptocurrency markets and enhances our model's explanatory power.

4.3 Fama-MacBeth (1973) Regression Analysis

In this section, we conduct a Fama-MacBeth cross-sectional regression analysis. We begin by categorizing each cryptocurrency into one of five portfolios based on their respective characteristics. These characteristics include $|\beta^i_{\Delta CryptoSent}|$, MCAP, and R 3,0, as 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 the Fama-MacBeth regression analysis, focusing on individual characteristics. Models (1) to (3) demonstrate statistically significant slopes, indicating that these specific factors have explanatory power for cross-sectional returns in the cryptocurrency market. In Panel B, models (4) to (6) incorporate the market beta (β_{CMKT}) in two-characteristic regressions. The outcomes are closely aligned with those in Panel A, where sentiment-sensitivity ($|\beta^i_{\Delta CryptoSent}|$), market capitalization (MCAP), and the 3-day return (R 3,0) continue to exhibit significant slopes.

Transitioning to Panel C, models (7) to (11) delve into more comprehensive Fama-MacBeth regressions that involve more than three characteristics. All slopes associated with $|\beta^i_{\Delta CryptoSent}|$ are statistically significant, showcasing t-statistics higher than 5.65 in absolute values. This emphasizes the critical role of sentiment in explaining the cross-sectional returns in the cryptocurrency market. Notably, the significance of β_{CMKT} diminishes across all models in Panel C, diverging from previous findings that utilized value-weighted portfolio strategies. This discrepancy might stem from the Fama-MacBeth regression's approach of treating each observation equally, mirroring the effect of equally weighted portfolios, thereby explaining the variation in results.

Model (10) revisits the three-factor model proposed by Liu and Tsyvinski (2022), highlighting significant alpha in the Fama-MacBeth regression analysis. In contrast, model (11) introduces our four-factor model, incorporating the sentiment factor. This addition enables our model to account for cross-sectional variation in returns with an insignificant alpha (-0.003), underscoring the substantial influence of sentiment in the weekly cross-sectional Fama-MacBeth regression.

In summary, the sentiment factor significantly improves the cross-sectional regression fit, proving to be a pivotal element in explaining the variations in cross-sectional returns within the cryptocurrency market.

4.4 PCA Analysis of Cryptocurrency Returns

In this section, we undertake a principal component analysis (PCA) on the eight significant long-short strategies previously discussed. We test whether a small number of principal components can capture the variation of the strategies' returns. Our analysis reveals that four principal components account for the majority of the variation in the returns of these strategies. Further, we explore the correlations between these four principal components and the four identified cryptocurrency factors, aiming to understand the relationships and influences among them.

[Insert Table 9 Here]

Table 9 presents results of the principal component analysis (PCA) conducted on eight significant long-short strategies. In Panel A, the table outlines the proportion of variance each principal component accounts for. Specifically, the first four principal components explain 30%, 24%, 11%, and 11% of the variance, respectively, cumulatively accounting for over 75% of the variation in the returns of the eight long-short strategies.

Panel B presents a correlation matrix between these first four principal components and the four cryptocurrency factors identified in our model. Notably, the first principal component exhibits a strong positive correlation (50.54%) with the cryptocurrency momentum factor. The second principal component is significantly linked (36.36%) to the size factor within the cryptocurrency market. The third principal component shows a robust positive correlation (52.36%) with the cryptocurrency sentiment factor. Conversely, the fourth principal component is negatively correlated with the market factor (-21.30%) and the sentiment factor (-49.97%).

In conclusion, the PCA reveals that a substantial portion of the variation in the eight long-short strategies is captured by the first four principal components. Moreover, the correlation patterns between these components and the cryptocurrency market factors align closely with our theoretical expectations, underscoring the consistency of our model with the observed market dynamics.

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. Drawing on the findings of Stambaugh, Yu, and Yuan (2012), which highlight the susceptibility of the short leg in long-short strategies to market sentiment, our study extends this analysis to the realm of cryptocurrencies. Similarly, Baker and Wurgler (2006) demonstrate that stocks characterized by certain features—such as being small, young, high volatility, unprofitable, non-dividend-paying, extremely growth-oriented, or distressed—tend to perform differently based on the prevailing market sentiment at the beginning of the period. Specifically, these categories of stocks generally yield higher subsequent returns when initial sentiment is low and lower returns when sentiment is high. Applying the sentiment index constructed in our paper, we explore the conditional returns of various cryptocurrencies, categorized by distinct characteristics, in response to sentiment levels. We presents our results in the following Figure 4.

[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
$\lvert\beta_{SENT}\rvert$	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

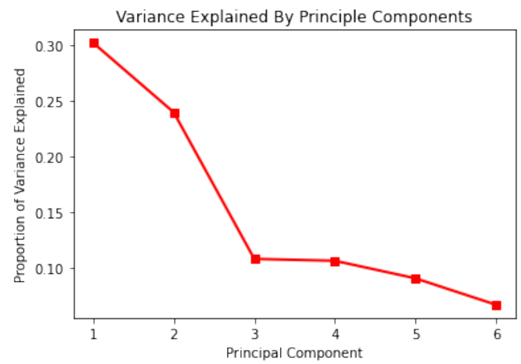
Panel C. Size Quintiles' Weighted Average Exposures on Sentiment $\|\beta^i_{\Delta CryptoSent}\|$					
	Quintiles				
	1	**2**	**3**	**4**	5
MCAP	**Low**				**High**
Mean	0.121	0.117	0.104	0.093	0.020

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}	$\|\beta^i_{\Delta CryptoSent}\|$	**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}	$\|\beta^i_{\Delta CryptoSent}\|$	**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}	$\|\beta^i_{\Delta CryptoSent}\|$	**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.

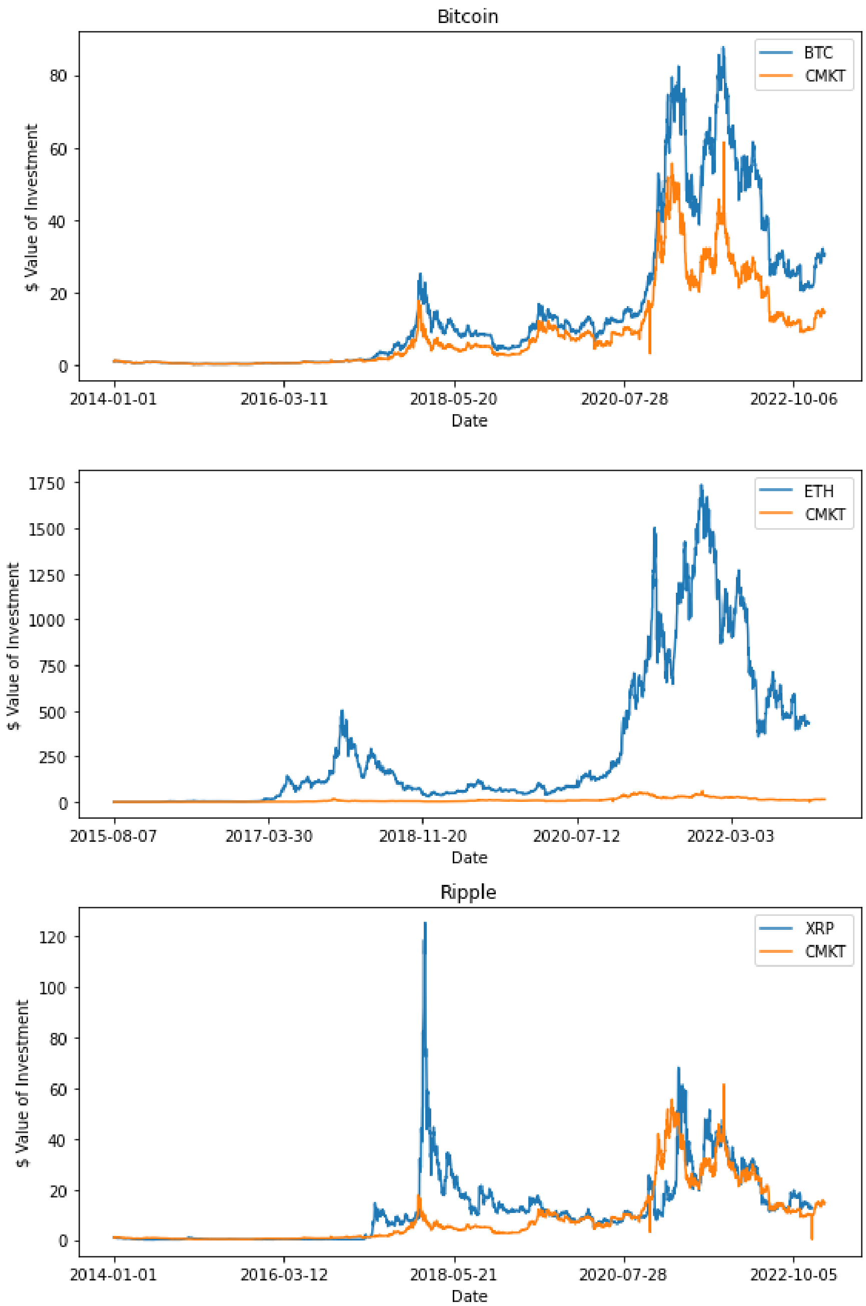
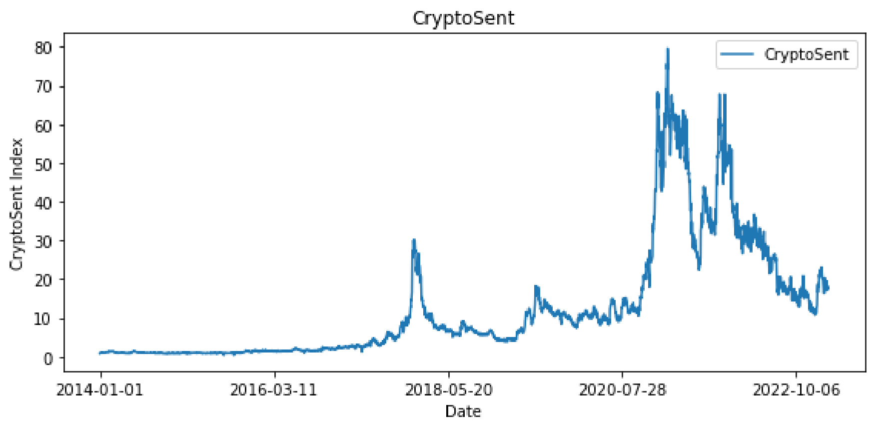


Figure 2: Cryptocurrency Sentiment Index CryptoSent Time Series Plot. Figure 2 Panel A plots the time series of Sentiment Index CryptoSent, including the cryptocurrency market index, market volatility, market volume, google trends, tweets discussion and number of active wallets on blockchain. The Cryptosent 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

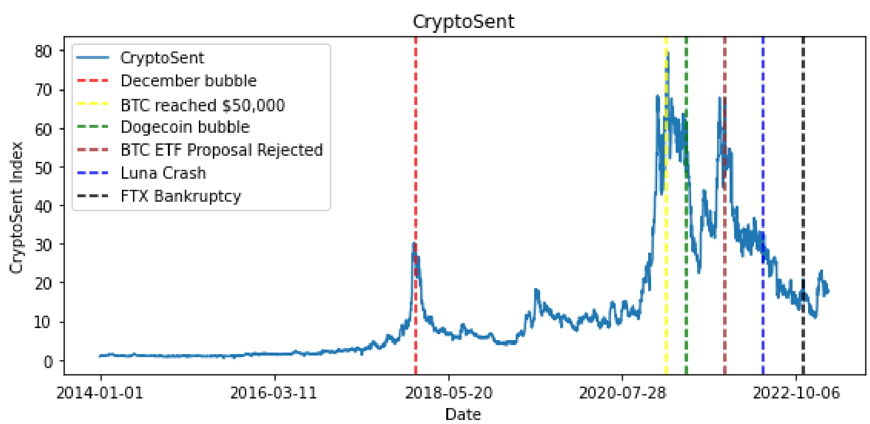


Figure 3: Cryptocurrency Sentiment Index CryptoSent Components.
Figure 3 plots the components of Sentiment Index CryptoSent, including the cryptocurrency market index, market volatility, market volume, google trends, tweets discussion and number of active wallets on blockchain. All these components are 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.

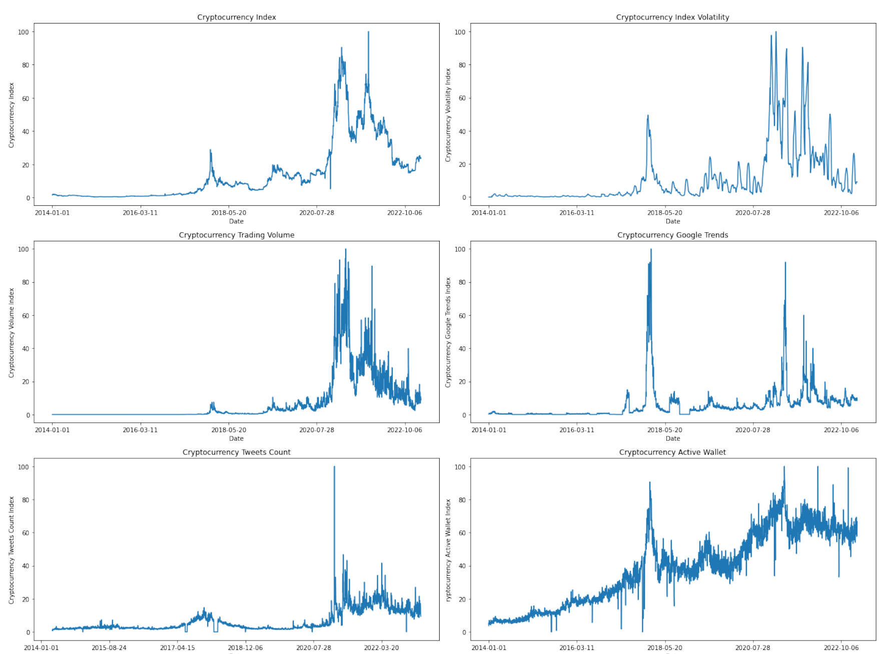
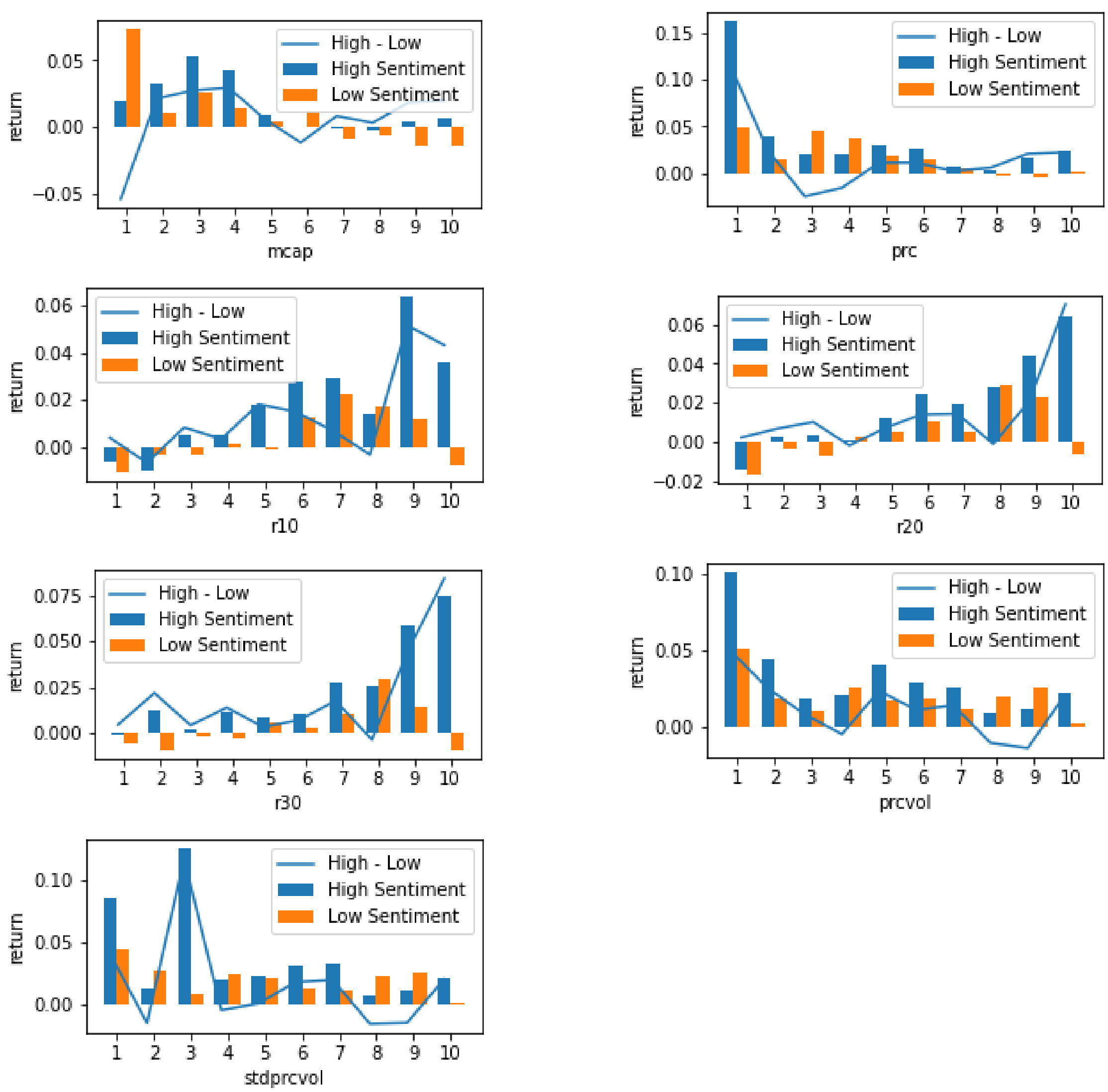


Figure 4: Long Short Portfolio Strategy Conditional on Long-Short Leg.
Figure 4 presents the future weekly return by sentiment index and firm characteristics. Each week, we categorize the sentiment index as high or low based on whether the latest $\Delta CryptoSent$ is above or below its median, respectively. 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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