Fundamental vs. Technical Analysis: News-based Factors and Cryptocurrency Risk Premia

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Abstract

This paper investigates the cross-sectional predictive ability of text-based factors in the cryptocurrency market, an important asset class for retail and institutional investors. We employ Bidirectional Encoder Representations from Transformers (BERT) topic modeling to analyze news articles discussing the top 43 cryptocurrencies by market capitalization. We build text-based factors related to fundamentals and technical trading and find that pessimism about technical news is positively priced in the cross-section of cryptocurrency returns, while pessimism about fundamental news is negatively priced. These factors provide information beyond existing factor models. Our results demonstrate the importance of considering text-based factors when analyzing cryptocurrency returns.

Keywords: cryptocurrency, fundamentals, media coverage, textual analysis.

JEL Classification: G11, G12, G14, G32.

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1 Introduction

This paper examines the cross-sectional predictive ability of text-based fundamental and technical trading measures in the cryptocurrency market. The market capitalization of this market exceeded 3 trillion USD in November 2021, with a total trading volume for spot and futures contracts of 8.8 trillion USD in the first quarter of 2020 (e.g., Helms, 2020). Cryptocurrencies are an important asset class for investors (e.g., Harvey, Abou Zeid, Draaisma, Luk, Neville, Rzym, and Van Hemert, 2022). Retail and institutional traders populate this market, which has experienced large price movements over the previous years. The lack of adequate market regulation and information quality has led many investors to link cryptocurrencies with market manipulation and fraud (e.g., Gandal, Hamrick, Moore, and Oberman, 2018). Other investors view this market as an important innovation, and its underlying blockchain technologies impact the financial system. However, the risk and return tradeoffs of cryptocurrencies and their mispricing sources are not well understood.

Building on the work of Liu, Tsyvinski, and Wu (2022) and Cong, Karolyi, Tang, and Zhao (2021), we develop a novel text-based factor-pricing framework that significantly improves our understanding of the cross-section of cryptocurrency returns. To the best of our knowledge, we are the first to construct text-based factors in the cryptocurrency market. We collect news articles from Factiva that mention the top 43 cryptocurrencies by market capitalization as of December 2021. We then implement Bidirectional Encoder Representations from Transformers (BERT) topic modeling to identify the most prominent topics. We identify topics that are related to fundamentals, technical trading, regulation, lending, payments, derivatives, social media, and hedging. We find that the most important text-based measures are factors that capture fundamentals and technical trading. This finding is in line with Filippou, Rapach, and Thimsen (2023), who find that fundamentals and technical trading rules are the most important out-of-sample predictors of cryptocurrency returns.

Therefore our analysis focuses on the sentiment of articles that discuss issues related to fundamentals and technical trading. We label the sentiment of the articles classified as technical or fundamental by the BERT model as the Technical Sentiment Index (TSI) and Fundamental Sentiment Index (FSI), respectively. Our measure of sentiment is based on the difference in frequency between negative and positive words based on the Loughran and McDonald (2011) measure. This measure captures net negative sentiment (or pessimism) on fundamental and technical topics.

Technical topics in our classification characterize whether we are in a cryptocurrency bull or bear market and refer to a discussion of trading strategies investors can use to exploit historical patterns in the data. Fundamental topics typically refer to factors affecting the demand and supply of a currency. On the supply side, important factors include the hash rate, which measures the computational power of a blockchain network. Other aspects of fundamentals are the technology of mining and the costs of executing transactions on the blockchain, such as gas fees on the Ethereum blockchain. On the demand side, fundamentals like the number of addresses and institutional factors such as demand for liquidity in exchanges matters.

We then find empirical evidence that the technical-based sentiment (TSI) is *positively* priced in the cross-section of cryptocurrency returns. This aligns with our conjecture that cryptocurrencies with positive exposure to technical analysis are riskier. Currencies that are more exposed to negative sentiment about technical trading have higher expected returns. The positive risk premium is consistent with risk compensation for investors holding cryptocurrencies that are more exposed to negative news about the state of the market and historical price patterns.

On the other hand, we find that fundamental-based sentiment (FSI) is *negatively* priced in the cross-section of cryptocurrency returns. The rationale behind this finding is that cryptocurrencies with positive exposure to fundamental analysis are overvalued, so investors pay a risk premium for holding these cryptocurrencies. The intuition is that negative sentiment on fundamentals indicates the currency has weaker supply and demand fundamentals. This could be a lower hash rate, indicating lower security of the network, or alternatively, a reduction in the number of addresses using the currency as a medium of exchange.

To examine the predictive ability of technical sentiment (TSI) and fundamental sentiment (FSI), we form long-short portfolios based on the exposure of each cryptocurrency to these factors, and sort cryptocurrencies into terciles every week based on their 60-week rolling betas. Then we form long-short portfolios that buy cryptocurrencies with high exposure to TSI and sell cryptocurrencies with low exposure to this factor (HML_{TSI}). Similarly, we buy cryptocurrencies with low exposure to fundamentals and sell cryptocurrencies with high FSI betas (LMH_{FSI}). Both strategies offer positive and statistically significant returns that are higher than the cryptocurrency market return. The Sharpe ratio of the technical sentiment strategy is 1.30, and it is 1.22 for the fundamental sentiment strategy.

We provide four sets of results with our technical and fundamental text-based factors. First, we show that conventional cryptocurrency risk factors cannot explain the returns of the text-based factors. We contemporaneously regress the technical and fundamental spread portfolios on the market, size, momentum, liquidity, and volatility factors and find that both strategies offer alphas that are statistically and economically significant. Following Cong et al. (2021), we also consider different value factors, based on the number of transactions recorded, the cumulative number of addresses to date created on the and the number of addresses with balance. and we find that the text-based technical and fundamental factors provide positive and statistically significant alphas. We show that text-based fundamental and technical sentiment factors are priced in the cross-section of cryptocurrency returns offering information over and above other existing factor models in the literature.

Second, we show that our fundamental and technical factors correlate with value factors defined in Cong et al. (2021). This suggests that our factors capture value measures, such as the ratio of addresses, hash rate, and volume of transactions to market cap, and supports our theory that fundamental news is linked to the mispricing of currencies.

Third, we conduct Fama and MacBeth (1973) cross-sectional regressions to test the pricing ability of the technical and fundamental factors after controlling for different determinants of cryptocurrency returns. We find that both factors are strong predictors of cryptocurrency returns even after controlling for other characteristics. In a baseline model which includes a market factor and text-based factors, we find the price of risk for the technical trading factor is 1.2 percent, and the price of risk for the fundamental factors is -1.2 percent. Our risk premia estimates are robust to adding alternative factor models that include volatility and momentum based on Liu et al. (2022) and Cong et al. (2021).

Finally, we conduct a number of additional robustness tests. Our results are robust when considering a smaller sample of a group of 15 cryptocurrencies with the highest market capitalization. Placebo tests using alternative topics on regulation, lending, derivatives, payments, social media, and hedging, cannot explain the cross-section of cryptocurrency returns. Our results are also robust to the choice of negative sentiment proxy and different specifications to estimate factor betas.

Literature review. Our paper contributes to an emerging literature explaining the cross-section of cryptocurrency returns (Bianchi and Babiak, 2021; Cong et al., 2021; Liu et al., 2022; Filippou et al., 2023; Bhambhwani, Delikouras, and Korniotis, 2021; Schwenkler and Zheng, 2020; Kogan, Makarov, Niessner, and Schoar, 2022; Bianchi, Babiak, and Dickerson, 2022; Han, Newton, Platanakis, Sutcliffe, and Ye, 2022; Luo, Mishra, Yarovaya, and Zhang, 2021).

The seminal work in Liu et al. (2022) establishes that cryptocurrency return factors based on market, momentum, and volatility have pricing power for the cross-section. However, in addition to return-based factors, Bhambhwani et al. (2021), and Cong et al. (2021) establish that value and network-based factors have sufficient explanatory power for cryptocurrency returns. In particular, blockchain characteristics relating to the hash rate and the number of addresses transacting with the network correlate positively with cryptocurrency prices.

Higher exposure to these characteristics can, in turn, lead to higher expected returns, which provide investors with a risk premium. Our work is differentiated because we infer our fundamental and technical factors directly from news on cryptocurrency articles. This decomposition allows us to disentangle alternative theories of cryptocurrency pricing more accurately and whether retail trading dominates it (e.g., Kogan et al., 2022) or by news on blockchain characteristics.

News in cryptocurrency markets has been used in prior work (Filippou et al., 2023; Schwenkler and Zheng, 2020). Schwenkler and Zheng (2020) use a textual analysis method to determine peer co-movement in cryptocurrency markets and document competition effects, where negative news about a peer can lead to substitution toward currencies that have similar network and blockchain characteristics. Filippou et al. (2023) use a variety of news sources (Factiva, Reddit comments, google trends) to develop return characteristics in a machine-learning model for forecasting cryptocurrency returns. The novelty of our paper in the textual analysis is using the BERT model to obtain text-based factors using cryptocurrency news. We measure the net sentiment in these topics to construct indices that measure pessimism about fundamental and technical news. Using standard asset pricing tests, we find both factors are priced in the cross-section of cryptocurrency returns and support alternative models that use value factors and blockchain characteristics.

The paper is organized as follows. Section 2 discusses the theoretical motivation and testable hypotheses of the paper. Section 3 outlines the data and definitions, including using BERT to identify cryptocurrency topics and constructing sentiment measures for technical and fundamental news. Section 4 outlines our main empirical asset pricing tests. Section 5 concludes.

2 Testable Hypotheses

Fundamental and technical analysis are two important concepts in the literature. Fundamental analysis provides a framework that can help investors identify the intrinsic value of an asset by examining different related economic and financial factors. At the same time, technical trading relies more on patterns of past prices to estimate future prices. In efficient markets, all available information should be incorporated into prices. However, empirical evidence suggests that stock prices deviate from their fundamental values, which makes fundamental analysis valuable (e.g., Fama, 1995; Abarbanell and Bushee, 1997; Yan and Zheng, 2017; Sloan, 2019). In addition, a lack of information about the fundamentals of an asset could lead investors to rely more on technical trading (e.g., Han, Zhou, and Zhu, 2016; Detzel, Liu, Strauss, Zhou, and Zhu, 2021). These concepts are particularly important in the cryptocurrency market because market inefficiencies make fundamental and technical trading highly profitable (Detzel et al., 2021). We propose two text-based factors that capture the sentiment of discussions in the media about fundamental and technical trading and test the importance of these concepts in the cryptocurrency market.

Hypothesis 1 (H1). *Cryptocurrencies with high pessimism about fundamentals are overvalued.*

(a.) Fundamental sentiment should negatively predict the cross-section of cryptocurrency returns.

(b.) Investors pay a risk premium for holding these cryptocurrencies.

There is growing evidence in the equities literature emphasizing that prices do not immediately incorporate publicly available information, such as earnings news (Sloan, 1996). Investors exploit this type of 'mispricing' by engaging in fundamental analysis. This refers to the practice of analyzing the financial statements of a firm to estimate the underlying firm value and compare it with its market price. For example, Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997) demonstrate that signals, which capture information on firm fundamentals such as inventory changes, gross margins, selling expenses, capital expenditures, effective tax rates, inventory methods, and labor force sales productivity, are associated with different rules of fundamental analysis used by financial analysts to forecast future firm performance. Abarbanell and Bushee (1998) build a trading strategy in the equities market using fundamental analysis signals and find that it offers abnormal returns.

As it is highlighted in Liu, Tsyvinski, and Wu (2021), in contrast to the equities market that has the Generally Accepted Accounting Principles (GAAP) standards for financial measurements, the cryptocurrency market does not have a standardized accounting framework to provide such measures. Accordingly, Luo et al. (2021) show that ambiguity is a factor that prices the cross-section of crytpocurrency returns. The lack of such information constitutes a challenge for traders and regulators to identify the fundamental value of cryptocurrencies.

However, there is a rich information set that is publicly available about economic activities in the blockchain. This information – which is available in real-time to investors and can be verified by examining the public ledger – can be useful in determining the intrinsic value of a cryptocurrency. For example, Liu et al. (2021) apply accounting and finance valuation frameworks to the cryptocurrency market. They find that information related to new addresses is highly value-relevant for cryptocurrencies. Bhambhwani et al. (2021) find evidence that both the number of addresses and the hash rate are robust predictors of cryptocurrency returns, and Cong et al. (2021) argue that these blockchain characteristics can be used as value-based factors.

We argue that discussions about cryptocurrency fundamentals in the news provide important information about the fundamental value of cryptocurrencies. Investors could utilize this information to determine the fundamental value of cryptocurrencies as it includes discussions from experts on the market about the economics of the blockchain and demand and supply dynamics. We conjecture that cryptocurrencies with negative fundamental news sentiment are overvalued, and cryptocurrencies with positive news sentiment are undervalued. Therefore investors pay a premium for holding cryptocurrencies with high fundamental pessimism.

Hypothesis 2 (H2). *Cryptocurrencies with high pessimism about technical analysis are riskier.*
(a.) Technical sentiment should be a positive predictor of the cross-section of cryptocurrency returns.
(b.) Investors require a risk premium for holding these cryptocurrencies.

The absence of observable fundamentals could lead investors to rely more on price patterns. In imperfect markets, Treynor and Ferguson (1985), Brown and Jennings (1989), Hong and Stein (1999), Cespa and Vives (2012), Edmans, Goldstein, and Jiang (2015), Han et al. (2016), Keloharju, Linnainmaa, and Nyberg (2019) show that past stock prices offer important information for future prices. This finding implies that technical indicators, which are based on past prices, could be important trading signals. Brock, Lakonishok, and LeBaron (1992) and Lo, Mamaysky, and Wang (2000) show empirical evidence that technical indicators are profitable signals in the stock market.

We argue that discussions in the media about price movements have strong implications for technical trading in the cryptocurrency market. This is particularly important in the absence of a standardized accounting framework that could offer reliable financial measurements. For example, Detzel et al. (2021), among others, focus on the bitcoin and find that 1- to 20-week moving averages of daily prices forecast bitcoin returns in-sample and out-of-sample. They show theoretically in an equilibrium model that when there is uncertainty about growth in fundamentals, rational learning by investors with different priors could lead to strong predictability of returns by moving average rules. Therefore, we conjecture that the sentiment of discussions about price movements from experts in the media should be positively priced in the cross-sectional of cryptocurrency returns. In other words, cryptocurrencies with high technical sentiment are riskier, and investors should require a risk premium for holding them.

3 Data and Definitions

This section discusses cryptocurrency data. We provide a detailed description of our corpus, the topic modeling approach, and the construction of the technical and fundamental sentiment indexes.

3.1 Cryptocurrency Data

We collect daily cryptocurrency data from CoinMetrics, which includes prices and other cryptocurrency characteristics data. CoinMetrics provides quality data on cryptocurrency characteristics. We begin with 50 cryptocurrencies with the highest market capitalization as of January 2022. Then we eliminate five stablecoins and two coins that are pegged to bitcoin.[1] Therefore our sample contains 43 cryptocurrencies. The data span the period of June 2017 to December 2021. We convert our data to weekly series by setting Friday as the end of the week to be consistent with the Fama and French factors convention. Therefore we construct weekly returns by calculating the difference between the closing price on the Friday of a week and the closing price on the Friday of the previous week.[2]

Table A1 of the Internet Appendix offers summary statistics of the data per year. Specifically, we report the total number of cryptocurrencies per year, the total market capitalization at the end of the year (in Billion $), the ratio of the total market capitalization of our sample to the total market capitalization of the cryptocurrency market, the average volatility and the average number of accounts. Our sample of cryptocurrencies varies by year. The total number of cryptocurrencies increased from 20 in 2017 to 43 in 2021. Our sample covers at least 78% of the total market capitalization every year. Therefore it covers most of the representative cryptocurrencies in the market.

[1]We remove the following cryptocurrencies: Tether (USDT), USD Coin (USDC), Binance USD (BUSD), DAI (DAI), Paxos Standard (PAX), Wrapped Bitcoin (WBTC), renBTC (RENBTC).

[2]We construct returns at the weekly frequency to avoid outliers, and day-of-the-week effect as in Biais, Bisiere, Bouvard, Casamatta, and Menkveld (2020).

3.2 Newspapers

We collect newspaper articles from Factiva mentioning the top 43 cryptocurrencies by market capitalization as of December 2021. In particular, our search keywords are both the name and abbreviation of cryptocurrencies.[3] Our data span the period from June 2017 to December 2021. During this sample period, 27,382 articles satisfy our search criteria.

3.3 BERT topic modeling approach

Our goal is to extract the most prominent topic from the news articles. This way, we can reduce the noise in our estimates and obtain factors that provide useful information for the cross-section of cryptocurrency returns. More conventional topic modeling methods extensively used in the literature are Latent Dirichlet Allocation (LDA) and Latent Semantic Indexing (LSI). Despite their widespread usage, there are shortcomings associated with these methods. The most crucial is that LDA and LSI rely on the bag-of-word representation of documents, implying that word ordering and semantics are overlooked. On the other hand, the Bidirectional Encoder Representations from Transformers (BERT) modeling approach is a state-of-the-art topic modeling structure developed to overcome these shortcomings (e.g., Devlin, Chang, Lee, and Toutanova, 2018). It is, therefore, our choice of algorithm to explore the topics of our corpus.

BERT is built to pre-train deep bidirectional representations from the unlabeled text by joint conditioning on both the left and right context in all layers. As a result, the pre-trained

[3] Articles from Factiva are collected from the following 47 publications from around the world: *The Cointelegraph*, *CoinDesk.com*, *Blockonomi*, *Dow Jones Newswires*, *express.co.uk* (UK), *PR Newswire*, *CE Noticias-Financieras* (Latin America), *Investing.com*, *Financial Times*, *Reuters*, *iCrowdNewswire*, *The Wall Street Journal*, *M2 Presswire*, *The Independent*, *Blockchain.News*, *The Times* (UK), *Investor's Business Daily* (US), *The Telegraph* (UK), *MarketWatch*, *Brave New Coin*, *Sputnik News Service* (Russia), *Benzinga.com*, *Mondaq Business Briefing*, *Business Insider*, *CNN*, *Forbes*, *Business Wire*, *City AM* (London), *South China Morning Post*, *GlobeNewswire* (US), *Investment Weekly News*, *The Economic Times*, *ACCESSWIRE*, *Postmedia Breaking News* (Canada), *Hedge Week*, *Daily Mail*, *The Australian*, *Financial News* (Europe), *Exchange News Direct*, *Korea Times* (South Korea), *The Globe and Mail*, *Agence France Presse*, *Institutional Asset Manager*, *The Canadian Press*, *Barron's*, *Times of India*, *The New York Times*.

BERT model can be fine-tuned with just one additional output layer for a wide range of tasks, including topic modeling.

The input required from the BERT topic modeling approach is the corpus, which is the set of cryptocurrency news articles in our case. In the first step, Sentence Transformers are used to extract document embeddings. The pre-trained model we use to extract document embeddings is RoBERTa, developed by Liu, Ott, Goyal, Du, Joshi, Chen, Levy, Lewis, Zettlemoyer, and Stoyanov (2019). In particular, documents are embedded to create representations in vector space that can be compared semantically. The next step in this process is to apply the UMAP algorithm (McInnes, Healy, and Melville, 2018) to the document embeddings. The purpose of this step is to reduce dimensions and cluster similar documents. UMAP is used to reduce the dimensionality of the vectors to 5 with the size of the neighborhood set to 15. The number of nearest neighbors optimizes the balance between the local and global structure in the new embedding, and this value gives the best results in preserving the local structure. Semantically similar documents are also grouped in different clusters. The last step is topic creation based on a class-based variant of TF-IDF (Term Frequency–Inverse Document Frequency) (i.e., c-TF-IDF). At this stage, all documents in the same cluster are treated as a single document. c-TF-IDF, which is a score indicating the importance of a word for a particular cluster, is constructed based on the following equation:

$$c - TF - IDF_i = \frac{t_i}{w_i} \times log \frac{m}{\sum_j^n t_j} \tag{1}$$

where t_i is the frequency of term t in cluster i, and it is divided by the total number of words in the cluster w_i. This is multiplied by the logarithmically scaled fraction of the total number of n documents across all clusters m divided by the sum of occurrences of term t in all those documents. Words with top c-TF-IDF in each cluster help us label that cluster. We summarize the process in Figure 1.

[FIGURE 1 ABOUT HERE]

The output generated from BERT topic modeling for our corpus is 20 topics and the top 30 keywords for each topic. We summarize the keywords for the six topics we identify as having Technical content in Figure 2. We find words that capture bullish and bearish movements of cryptocurrencies, such as bulls, bears, and terms used in technical trading, such as chart, uptrend, levels, push, gains, visualization, losses, downside, swing, resistance, moving, average, volume, break, wave, line, and upside.

[FIGURE 2 ABOUT HERE]

We summarize the keywords for the topic we identify as having Fundamental content in Figure 3. We find that the most prominent words in this topic include words that describe fundamentals such as mining, hash, hash rate, operations, network, power, technology, securities, rate, hardware, and bitmain.

[FIGURE 3 ABOUT HERE]

3.4 Technical Sentiment Index and Fundamental Sentiment Index

BERT gives us a sample of news articles classified as having technical or fundamental content. We plot the raw number of technical news articles over time in Panel A and the number of fundamental news articles over time in Panel B of Figure 4. We can see that the number of fundamental news articles spikes around events such as the cryptocurrency mining malware in North Korea, the bitcoin mining blackout in China, or the crackdown on cryptocurrency mining by China.

[FIGURE 4 ABOUT HERE]

We calculate the sentiment of articles with fundamental or technical trading content. Specifically, we count the number of positive and negative words in Loughran and McDonald (2011) dictionary. We only compute the sentiment of the sentences that mention the specific cryptocurrencies in our dataset to reduce the noise in our measure. Therefore the sentiment takes the following form:

$$Sent = \frac{\text{Number of negative words-Number of positive words}}{\text{Total number of words}} \tag{2}$$

where $Sent$ denotes the technical sentiment (TSI) or fundamental sentiment (FSI). Therefore an increase in the sentiment measure indicates higher pessimism about fundamental or technical trading in the cryptocurrency market. An example of a technical trading sentence is "*monday, feb. 19: the bitcoin price has surpassed $11,000 twice since sunday as bullish sentiment returns to markets and new support begins to form*", with a sentiment measure of -0.17. An example of a fundamental trading sentence is "*coinhive reportedly had to shut down its services amidst a 50 percent decline in hash rate following the last monero hard fork.*", with a sentiment measure of 0.2.[4] Panel A shows the sentiment measure for technical trading, and Panel B shows the sentiment measure for the fundamentals index. We find that the measures move in opposite directions under specific periods, which suggests that fundamental analysis tends to be more successful in periods when technical trading is less profitable.

[FIGURE 5 ABOUT HERE]

Summary statistics of TSI and FSI are reported in Panel A in Table 1. FSI is characterized by a lower mean than the TSI index. Both indices are similar in terms of the second moment.

[4]For more details on the types of articles that are classified as technical or fundamental, we refer readers to Appendix A and B of the Internet Appendix. We also provide more examples of fundamental and technical article sentences and their sentiment scores.

FSI exhibits larger skewness and kurtosis. Both TSI and FSI are stationary according to the augmented Dickey-Fuller test. In Panel B of the same table, correlations between TSI and FSI and some other prominent risk factors in the cryptocurrency pricing literature are reported. Our TSI and FSI indices are unrelated to the size, momentum, liquidity, and volatility factors. TSI has a mild negative correlation of -0.27 with the market factor, whereas the correlation between FSI and the market factor is even lower (-0.18). Importantly, TSI and FSI have a negligible correlation of 0.04. Overall results in this table suggest that TSI and FSI capture different dimensions of risks compared with other conventional risk factors in the literature.

[TABLE 1 ABOUT HERE]

4 Empirical Results

4.1 Portfolio construction

To test whether the technical and fundamental sentiment indexes contain important information for the cross-section of cryptocurrency returns, we sort cryptocurrencies into portfolios based on their exposure to TSI and FSI.

Rolling Betas. To measure the exposure of each cryptocurrency to TSI (and FSI), we regress individual cryptocurrency excess returns at time t on a constant and SI (TSI or FSI), controlling for other cryptocurrency risk factors. These risk factors include the cryptocurrency market factor (MKT), size factor (SMB), momentum factor (MOM), volatility factor (VOL), and liquidity factor (LIQ).[5] The estimation is based on a 60-week rolling window. The time-varying slope coefficient obtained from this regression is $\beta_{i,t}^{TSI}$ (and $\beta_{i,t}^{FSI}$). Specifically, we estimate the model below:

[5]Description of risk factors can be found in Table A2 of the Internet Appendix.

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{SI} SI + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{MOM} MOM_t + \beta_{i,t}^{VOL} VOL_t + \beta_{i,t}^{LIQ} LIQ_t + \epsilon_{i,t}, \quad (3)$$

where $rx_{i,t}$ is the cryptocurrency return at time t, SI represent the TSI or FSI factors and our control variables. We include controls in the regression to account for other determinants of cryptocurrency returns.

Technical Sentiment Portfolios. At time t, we sort cryptocurrencies into terciles based on their previous week (i.e. $t-1$) betas with TSI. We limit the number of portfolios to four to have a reasonable number of currencies in each portfolio. We rebalance our portfolios weekly. The first portfolio (P_1) includes currencies with the lowest betas, while the fourth portfolio (P_4) covers currencies with the highest betas. We then construct a zero-cost portfolio (HML_{TSI}), which goes long the high beta portfolio (P_4) and short the low beta portfolio (P_1).

Fundamental Sentiment Portfolios. At time t, we sort cryptocurrencies into terciles based on their previous week (i.e. $t-1$) betas with FSI. We rebalance our portfolios weekly. The first portfolio (P_1) includes currencies with the lowest betas, while the fourth portfolio (P_4) covers currencies with the highest betas. We then construct a zero-cost portfolio (LMH_{FSI}), which goes long the first portfolio (P_1) and short the high beta portfolio (P_4).

4.1.1 Summary Statistics

If TSI (and FSI) is a pricing factor for the cross-section of cryptocurrency returns, there should be a significant dispersion in excess returns between low-beta and high-beta portfolios. Therefore the corresponding spread portfolio HML_{TSI} (and LMH_{FSI}) should generate statistically significant excess returns. Table 2 reports summary statistics of portfolios sorted on β_{TSI} (Panel A) and β_{FSI} (Panel B).

Panel A shows that investing in cryptocurrencies with the lowest (highest) exposure to TSI (β_{TSI}) yields average negative (positive) excess returns. The average portfolio returns are monotonically increasing in the TSI beta. Average excess returns of the first portfolio (P1) are negative and statistically significant with a Newey and West (1987) t-statistic of 2.55. The average excess returns to HML_{TSI} portfolio is of particular interest, which is positive and statistically significant with a Newey and West (1987) t-statistic of 2.54. The HML_{TSI} portfolio yields an annualized average excess return of 65.6% with a Sharpe ratio of 1.30.

Panel B suggests a negative association between average portfolio excess returns and the FSI betas. The average excess returns are monotonically decreasing from P1 to P4. The LMH_{FSI} portfolio now generates a strong performance. This portfolio yields 61.3% excess returns annually on average (with a Newey and West (1987) t-statistic of 2.54) and a Sharpe ratio of 1.22.

[TABLE 2 ABOUT HERE]

We plot the cumulative returns of two strategies in Figure 6. We observe that both strategies are profitable and outperform the market portfolio. Specifically, the TSI trading strategy was very profitable at the beginning of our sample and from 2018 until 2021, and the fundamental sentiment strategy was more profitable than the technical strategy for a few months in 2018 and since 2021.

[FIGURE 6 ABOUT HERE]

We also plot the portfolio turnover in Figure 7. Panel A shows the frequency of cryptocurrencies in the low-beta TSI portfolios, and Panel B shows the portfolio turnover of cryptocurrencies in the high-beta TSI portfolios. Panel C and Panel D show the results for low and high FSI betas, respectively. We find the holdings of the two strategies are very different. The TSI strategy relies more on cryptocurrencies such as BCH, DOGE, and

XEM in the low TSI portfolio and LINK, QNT, and XRP in the high TSI portfolio. On the other hand, the FSI strategy is driven more by ADA, DOGE, LINK, and XLM in the low FSI portfolio and BAT, GNO, and NEO in the high FSI portfolio.

[FIGURE 7 ABOUT HERE]

4.1.2 Technical and Fundamental Sentiment Portfolios and Other Investment Strategies

In this section, we test whether our sentiment factors offer significant alphas after controlling for market, size, momentum, liquidity, and volatility risk factors. The first column in Panel A of Table 3 shows results for univariate regression in which market portfolio is the only independent variable. The coefficient of the market portfolio is negative but statistically insignificant, whereas the alpha is 1.3% monthly and statistically significant with a t-statistic of 2.55. These findings suggest that the market factor cannot explain our HML_{TSI} portfolios. In the next column, we add the size factor to the regression and find the same pattern. The coefficient of the market factor is insignificant, whereas the coefficient of the size factor is marginally significant. On the other hand, the regression's alpha remains economically and statistically significant at a t-statistic of 2.13. In the next regression, we augment the previous model with the momentum factor, and this factor's coefficient is statistically significant. The alpha in the regression maintains its statistical significance. We add the liquidity and volatility factors in the last two regressions, respectively. This does not change the statistical significance of alpha. Overall, we find that the HML_{TSI} strategy can generate a positive and statistically significant alpha even after considering conventional asset pricing models.

Panel B shows the link between LMH_{FSI} and other conventional investment strategies. In the first column, the market factor is the only independent variable. The coefficient of market factor is statistically insignificant, similar to what we find in Panel A. Alpha is 1.2%

monthly and statistically significant with a t-statistic of 2.58. We gradually add control variables and the statistical significance of alpha is even stronger. With the full set of control variables in the last column, alpha is 1.3% monthly with a t-statistic of 3.22. Our results suggest that the LMH_{FSI} strategy can generate a positive and statistically significant alpha even after considering conventional asset pricing models.

[TABLE 3 ABOUT HERE]

We then examine the link between HML_{TSI} and (LMH_{FSI}) and other fundamental related risk factors in the cryptocurrency literature. In particular, we test if our factors are explained by fundamental risk factors constructed in Cong et al. (2021). We regress HML_{TSI} and (LMH_{FSI}) contemporaneously on three value factors to see if these value factors can explain the returns generated by TSI (and FSI). Table 4 reports the results.

The table displays regression results with three independent variables: value factors constructed based on the transaction-to-market ratio (T/M), user-to-market ratio (U/M), and address-to-market ratio (A/M) respectively.[6] In Panel A, all three value factors have positive coefficients, indicating a positive relationship with the dependent variable, but the statistical significance values are not particularly strong. However, the constants in all three columns are positive and strongly significant. In Panel B, the relationship between the three value factors and LMH_{FSI} is investigated. The coefficients for all three value factors are positive and strongly significant, with t-statistics of 3.51, 3.55, and 2.98, respectively. This is intuitive and supports our hypothesis that our measure of fundamental sentiment is interpreted as an over-under valuation of a currency. The constants also remain positive and statistically significant in all regressions. Therefore, the results in Panel B highlight an important finding: while value factors are positively correlated with LMH_{FSI}, they cannot fully explain LMH_{FSI}. It means that LMH_{FSI} captures a different dimension of fundamental cryptocurrency characteristics beyond the three value factors.

[6] Description of risk factors can be found in Table A2 of the Internet Appendix.

[TABLE 4 ABOUT HERE]

We also show the results with network risk factors in Table A3. Similarly, network factors cannot explain either HML_{TSI} or LMH_{FSI}.

4.2 Asset Pricing Tests

4.2.1 Framework

We start with a framework to conduct our asset pricing tests. Under general conditions, there exists a stochastic discount factor (SDF) M_t, which can price the excess returns of any asset i, $rx_{i,t}$.

$$\mathbb{E}[M_t rx_{i,t}] = 0 \tag{4}$$

Following Bhambhwani et al. (2021), we assume the SDF is a linear function of observable factors F_t, where μ_F where f_t are factors centered around their means and b is a vector of parameters.

$$M_t = 1 - b'(F_t - \mu_F) \tag{5}$$

Using the equation for the SDF, we can write returns as a linear function of factor betas:

$$\mathbb{E}[rx_{i,t}] = \lambda' \beta_i, \tag{6}$$

where β_i measures the exposure of returns to factor i, and λ is a measure of the risk price associated with factor i.[7] We will use this standard linear-beta representation of the SDF

[7] $\beta_i = \mathbb{E}[(f_t - \mu_F)(f_t - \mu_F)']^{-1}\mathbb{E}[(f_t - \mu_F)' R_{i,t}]$ is the vector of factor betas for cryptocurrency i, and $\lambda = \mathbb{E}[(f_t - \mu_F)(f_t - \mu_F)']b$ is the vector of risk prices.

in cross-sectional regressions of expected returns on factor-beta. In our first method in section 4.2.2, we will use individual currencies as test assets and estimate the risk prices of our sentiment measures, TSI and FSI and whether it can explain the cross-section of cryptocurrency returns. We will then conduct a two-step Fama Macbeth regression in section 4.2.3, where we use portfolios sorted on lagged sentiment measures to estimate the risk price.

4.2.2 Estimating price of risk: panel regressions

Test assets. Our test assets are individual currencies rather than portfolios. Ang, Liu, and Schwarz (2018) suggest that grouping stocks into portfolios shrinks the betas' cross-sectional dispersion, which leads to a less efficient estimate of factor risk premia. Bali, Brown, and Tang (2017) estimate the risk price of economic uncertainty using individual stocks. In the context of currencies, Barroso, Kho, Rouxelin, and Yang (2018) test the risk price of global imbalances using individual currencies.

Cross-sectional Regressions. We now investigate the risk price of β^{TSI} (and β^{FSI}). Having estimated β^{TSI} (and β^{FSI}) from equation (3), we investigate the cross-sectional relation between these betas and expected excess returns at the cryptocurrency level (Bali et al., 2017). In particular, we run weekly cross-sectional regressions at each time t:

$$rx_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}^{SI}_{i,t} + \lambda_{2,t}X_{i,t} + \epsilon_{i,t+1}, \tag{7}$$

where TS denotes the TSI or FSI and $X_{i,t}$ is a set of control variables, including β^{MKT}, β^{Size}, $\beta^{Momentum}$, and $\beta^{Volatility}$ estimated from Equation (3). We then take the time-series average of slope coefficients $\lambda_{1,t}$ and report its Newey and West (1987) t-statistic and average adjusted R^2.

Table 5 summarizes results regarding the estimation of risk prices of the β^{TSI} (Panel A) and β^{FSI} (Panel B) from regressions (2) and (3). In this table, we report results for TSI in *Panel A*. The univariate regression results in the first column suggest a positive link between the β^{TSI} and the cross-section of future cryptocurrency excess returns. The market price of risk λ associated with the β^{TSI} is 0.005, with a t-statistic of 3.43. This positive coefficient for β^{TSI} implies that taking a long position in currencies with higher β^{TSI} predicts positive returns in the following period. To examine the economic significance of this result, we compute the difference in average β^{TSI} between P_1 and P_4 from Table 2, which is 3.42 [=1.78 - (-1.64)]. If a currency were to move from P_1 to P_4, its expected return would decrease by 1.71% [=3.42 × 0.005] per week. Therefore, the risk price of the β^{TSI} is not only statistically significant but also economically significant.

In the second column, when we control for β^{MKT}, the risk price of β^{TSI} remains positive and statistically significant with a Newey and West (1987) t-statistic of 3.52, and the risk price of β^{MKT} is statistically insignificant. The third column controls for $Size$ of individual cryptocurrencies, and it still gives us a positive and statistically significant risk price of β^{TSI}. On the other hand, $Size$ is statistically insignificant. In the fourth column, when adding $Momentum$ as a control, we still get a strongly significant risk price of APR with a Newey and West (1987) t-statistic of 3.75. In the fifth column, the presence of $Liquidity$ also doesn't impact the predictive power of β^{TSI}. In the sixth column, we add $Volatility$ as the last control variable. In this full specification, the risk price of β^{TSI} maintains its strongly positive significance with a Newey and West (1987) t-statistic of 3.55.

We report results for the FSI in *Panel B*. The univariate regression results shown in the first column suggest a negatively significant link between the β^{FSI} and the cross-section of future cryptocurrency excess returns. The coefficient of β^{FSI} is -0.004 with a t-statistic of -2.61. This negative coefficient for β^{FSI} is in line with the portfolio results shown in Table 2, meaning that taking a long position in currencies with lower β^{FSI} predicts positive returns in the following period. To examine the economic significance of this result, we compute the difference in average β^{FSI} between P_1 and P_4 from Table 2, which is -2.76 [=-1.36 - -1.40). If a currency were to move from P_1 to P_4, its expected return would decrease by 1.10% [=2.76 × 0.004] per week. Therefore, the risk price of the β^{TSI} is both statistically and economically significant. The β^{FSI} coefficient is robust to adding factors controlling for market, volatility and momentum. In the full specification, the risk price of β^{FSI} is -0.005 with a Newey and West (1987) t-statistic of -2.00.

[TABLE 5 ABOUT HERE]

Having found evidence of strong predictive power of β^{TSI} and β^{FSI} for the next week's cryptocurrency returns, we now test whether our sentiment factors have predictive power at a longer horizon. We regress the cryptocurrency excess returns from 2 weeks to 12 weeks ahead on β^{TSI} (and β^{FSI}) with the same set of control variables in the previous subsection. We report the results in Table 6.

In Panel A, it can be seen that the coefficient of β^{TSI} is positive and strongly significant in all 12 columns. Even with 12 weeks ahead, the predictive power of β^{TSI} is 0.004 with a Newey and West (1987) t-statistic of 2.38, showing that β^{TSI} is priced in the cross-section of cryptocurrencies beyond the horizon of 12 weeks. In Panel B, we observe the coefficient of β^{FSI} is negative and strongly significant up to 5 weeks ahead and gradually fades away.

[TABLE 6 ABOUT HERE]

4.2.3 Fama Macbeth Asset pricing Tests

We apply a Fama and MacBeth (1973) (FMB) two-pass regression. Our portfolios $P1$ to $P4$ are defined in section 4.1, and are constructed by sorting portfolios based on lagged values of β_{TSI} and β_{FSI} respectively. We then construct a measure of returns of the high beta portfolio (P4) less the returns of low beta portfolio (P1), HML_{SI}. For each sentiment measure, in the first stage, we run contemporaneous time-series regressions of currency portfolio excess returns on the risk factors. In our baseline specification, we only include the market factor. We conduct FMB two-pass regressions for a number of alternative specifications in section 4.2.4.

$$rx_{i,t} = \alpha_{i,t} + \beta_i^{SI} HML_{SI,t} + \beta_i^{MKT} MKT_t + \epsilon_{i,t}, \qquad i = P1, P2, P3, P4 \tag{8}$$

In the second stage, we perform cross-sectional regressions of average portfolio returns on factor loadings, calculated in the previous step, to obtain the factor risk prices.

$$\overline{rx}_i = \lambda_{0,i} + \lambda_i^{SI} \hat{\beta}_i^{SI} + \lambda_i^{MKT} \hat{\beta}_i^{MKT} + \epsilon_i \tag{9}$$

We report the results for a two-factor model that consists of the market factor (MKT) and the sentiment factors in Table 7. We provide estimates for the implied risk factor (λ) and the corresponding Newey and West (1987) t-statistic, the root mean square error (RMSE), and cross-sectional R-squared. In Panel A, we report the results for the TSI factor. We find that the TSI factor strongly predicts the cross-section of cryptocurrency returns, while the market factor is insignificant. The risk price λ^{TSI} is 1.2% per week with a Newey and West (1987) t-statistic of 2.52. The low RMSE of 0.0005 and R^2 of 0.99 suggests that our risk factor explains the model well.

In Panel B, we replicate the same methodology with the FSI factor. It can be seen from this panel that the risk price λ^{FSI} is -1.20% per week with a Newey and West (1987) t-statistic of -3.03. RMSE and R^2 of this regression are 0.0018 and 0.86, respectively. Overall, results in this section provide further evidence that λ^{TSI} and λ^{FSI} are priced in the cross-section of cryptocurrency returns. We also report t-statistics based on Shanken (1992) standard errors, which account for the error-in-variable problem – the fact the regressors of the second pass regression are estimated in the first pass regression. We find that our results remain highly significant at the 1% significance level.

[TABLE 7 ABOUT HERE]

4.2.4 How do TSI and FSI improve asset pricing models?

In this section, we explore the role of TSI and FSI in improving existing cryptocurrency asset pricing models. We augment a set of existing factor models with the TSI and FSI factors. Our test assets now include four portfolios each sorted by size, momentum, liquidity, volatility, TSI and FSI.

Table 8 reports the prices of risk and the corresponding t-statistics as well as the RMSE and the cross-sectional R^2 of the regression. In Panel A, we start with the one-factor CAPM cryptocurrency model. When MKT is the only risk factor, the risk price of this factor is statistically insignificant, which is consistent with findings in the literature. This model has RMSE of 0.004 and R^2 of 4.9%, which suggests that there is a large variation in the cryptocurrency returns not explained by the market factor. We then add two risk factors, HML_{TSI} and HML_{FSI}, to the one-factor model.[8] The prices of risk, λ^{TSI} and λ^{FSI}, are both statistically significant. λ^{TSI} shows a positive sign, whereas λ^{FSI} shows a negative sign. The RMSE of this model is 0.003, and R^2 is 43%. It suggests that adding HML_{TSI} and HML_{FSI} to the cryptocurrency CAPM model improves the asset pricing model both in terms of RMSE and R^2.

We then do the same exercise with the two-factor model (Panel B), three-factor model (Panel C), and five-factor model (Panel D). In all cases, adding HML_{TSI} and HML_{FSI} significantly improves the existing asset pricing models for cryptocurrencies, both in terms of RMSE and R^2. Our results remain significant after we consider t-statistics that are based on Shanken (1992) standard errors.

[TABLE 8 ABOUT HERE]

[8] Note here that we use a high-minus-low portfolio for the FSI index so as to have a sign that is consistent with our main findings.

4.3 Robustness tests

4.3.1 Top 15 cryptocurrencies

To ensure that smaller cryptocurrencies do not drive our results, we replicate the two strategies with the top 15 cryptocurrencies ranked by average market capitalization during our sample period.[9] We report the portfolio sorting results in Table 9.[10]

In Panel A, we show results when sorting cryptocurrencies based on β^{TSI}. The monotonic pattern is found between Portfolio 1 and Portfolio 3. HML_{TSI} generates an excess return of 0.65% annually with a Newey and West (1987) t-statistic of 2.11, and a Sharpe ratio of 1.04. In Panel B, we replicate our strategy with β^{FSI}. LMH_{TSI} portfolio achieves an excess returns of 0.65% annually with a Newey and West (1987) t-statistic of 2.0. The Sharpe ratio of this portfolio is 0.69. Therefore we provide evidence that our results are robust to the sample choice of cryptocurrencies.

[TABLE 9 ABOUT HERE]

4.3.2 Placebo test

To alleviate the concern that our results are due to data mining, we construct the sentiment index for other topics identified by BERT topic modeling. These topics include lending, regulation, payment, derivatives, social media, and hedging. Our results are in Table 10. The sentiment of these topics do not predict cross-sectional cryptocurrency returns, and the HML portfolios constrcuted using these factors are statistically insignificant.

[TABLE 10 ABOUT HERE]

[9] This sample includes Bitcoin, Bitcoin Cash, Cronos, Stellar, Dogecoin, Chainlink, Ethereum, Cardano, Ripple, Polkadot, Litecoin, Uniswap, Internet Computer, Algorand, FTX Token

[10] We limit the number of portfolios to three due to the limited number of cryptocurrencies available at the beginning of the sample.

4.3.3 Alternative proxies for sentiment

We construct alternative measures of sentiment of technical and fundamental trading factors to equation (2). One alternative is to use the number of negative words over the total number of words (equation (10)), or the net negative words over the total number of positive and negative words (equation (11)).

$$Sent = \frac{\text{Number of negative words}}{\text{Total number of words}} \tag{10}$$

$$Sent = \frac{\text{Number of negative words-Number of positive words}}{\text{Number of negative words+Number of positive words}} \tag{11}$$

We report the results for these two alternative proxies in Tables A4 and A5 of the Internet Appendix. The results suggest that these alternative measures of sentiment generate robust factors in predicting cryptocurrency returns.

4.3.4 Alternative specifications to estimate β^{TSI} and β^{FSI}

We estimate β^{TSI} and β^{FSI} based on alternative specifications to equation (3), which uses 5 factors, market, size, momentum, volatility and liquidity in addition to the sentiment factor. In the first alternative specification, we only control for the market (MKT) factor when we estimate the betas. The model takes the following form:

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{SI} SI + \beta_{i,t}^{MKT} MKT_t + \epsilon_{i,t}, \tag{12}$$

We also consider a specification with the market (MKT), size (SMB), and momentum (MOM) factors. The model takes the form below:

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{SI} SI + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{MOM} MOM_t + \epsilon_{i,t}, \tag{13}$$

where SI denotes the FSI or TSI. We then construct the long-short strategy based on past β^{TSI} and β^{FSI}. Summary statistics of portfolios for specification (12) and (13) are shown in Tables A6 and A7 respectively of the Internet Appendix. Constructing long-short portfolios always generate positive and statistically significant returns when alternative specifications to estimate β^{TSI} and β^{FSI} are used. Therefore our fundamental and technical sentiment factors are robust to including alternative factor models as controls.

5 Conclusion

This paper investigates the cross-sectional predictive ability of text-based fundamentals and technical trading measures in the cryptocurrency market. We develop a novel text-based factor-pricing framework that significantly improves our understanding of the cross-section of cryptocurrency returns. We collect news articles that mention the top 43 cryptocurrencies by market capitalization and implement Bidirectional Encoder Representations from Transformers (BERT) topic modeling to identify the most prominent topics related to fundamentals, technical trading, regulation, lending, payments, derivatives, social media, and hedging. We then identify factors that capture fundamentals and technical trading and analyze their sentiment using a difference in frequency between negative and positive words.

We find that the most important text-based measures are factors that capture fundamentals and technical trading. Technical analysis can help investors exploit historical patterns in the data to determine whether the market is in a bull or bear phase. On the other hand, fundamental analysis considers factors affecting the demand and supply of a cryptocurrency, including hash rate, mining technology, transaction costs, and institutional demand for liquidity.

We find that technical-based sentiment (TSI) is positively priced in the cross-section of cryptocurrency returns, suggesting that cryptocurrencies with positive exposure to technical analysis are riskier and have higher expected returns. Conversely, fundamental-based sentiment (FSI) is negatively priced in the cross-section of cryptocurrency returns, indicating that cryptocurrencies with positive exposure to fundamental analysis are overvalued and have weaker supply and demand fundamentals. Negative sentiment on fundamentals can result from lower hash rates or a reduction in the number of addresses using the currency as a medium of exchange.

We show that the text-based fundamental and technical sentiment factors are priced in the cross-section of cryptocurrency returns, offering information over and above other existing factor models in the literature. In sum, our findings have important implications for investors in the cryptocurrency market, and highlight the importance of considering fundamental and technical sentiment factors in their investment decisions.

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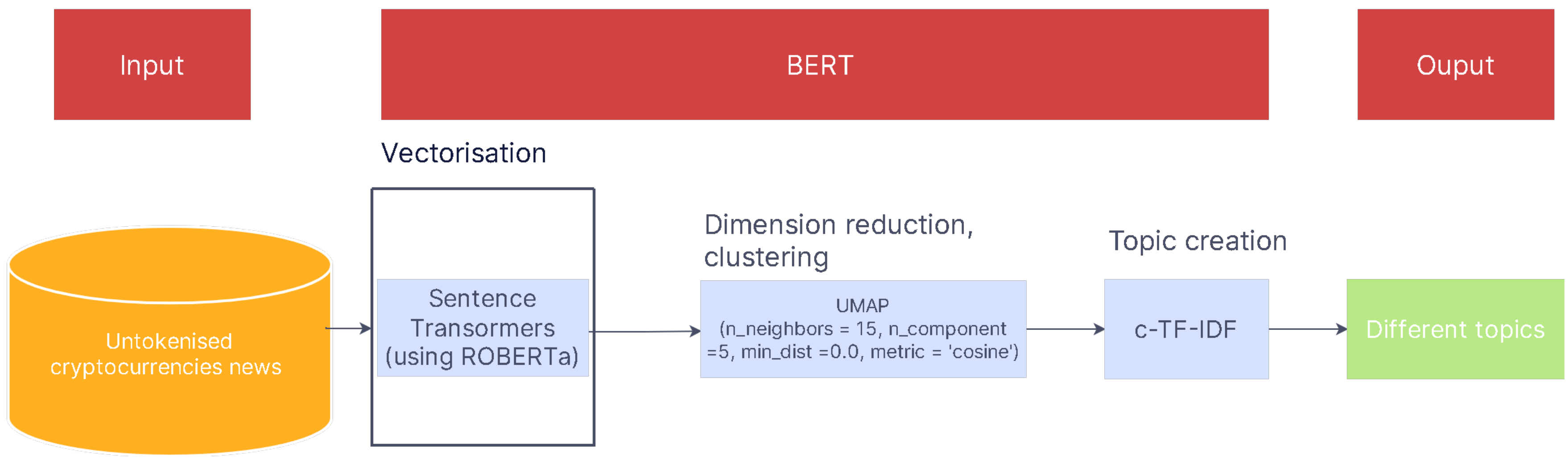
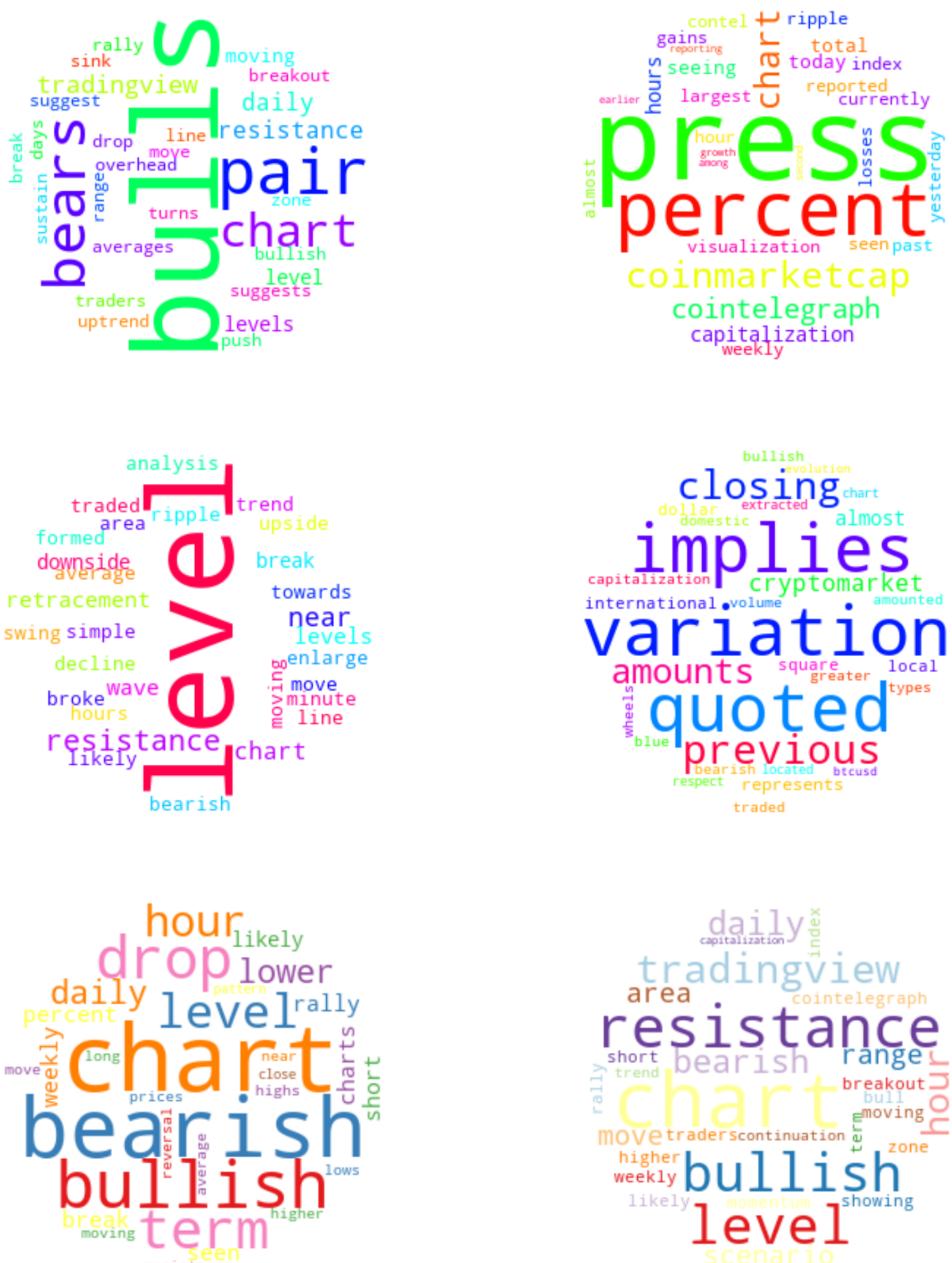
Figure 1. BERT modelling



This graph shows a summary of the BERT algorithm.

Figure 2. Technical Topics generated from BERT topic modelling

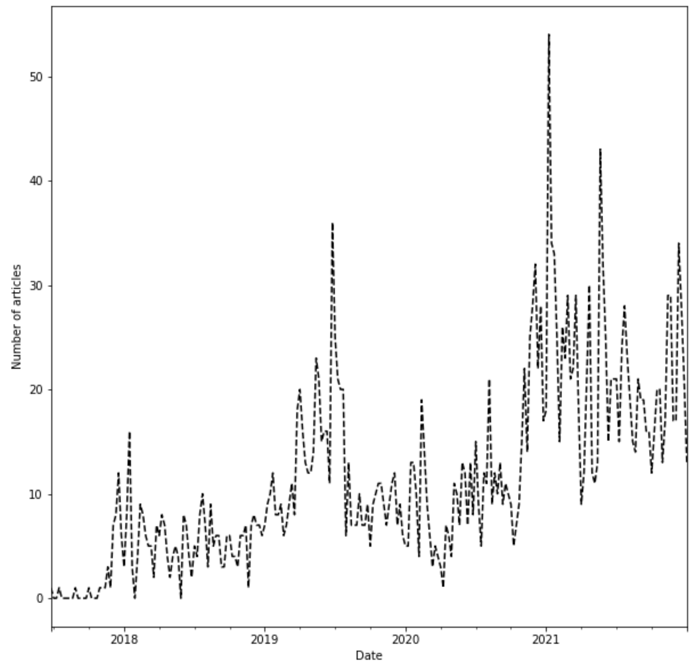


The figure shows keywords for 6 Technical topics. The topics are generated from BERT topic modelling algorithm based on Factiva news articles about cryptocurrencies between June 2017 and December 2021.

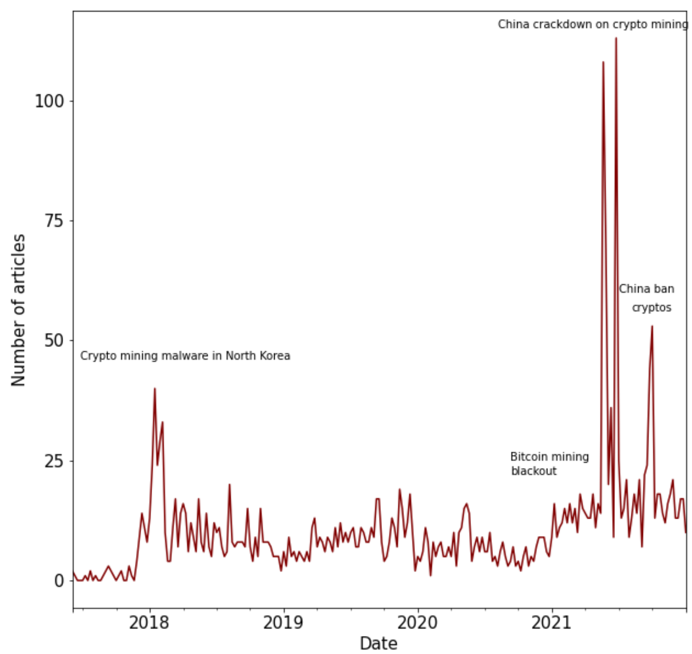
Figure 3. Fundamental Topic generated from BERT topic modeling

This graph shows keywords for the Fundamental topic. The data is weekly between June 2017 and December 2021.

Figure 4. Technical and Fundamental News Articles



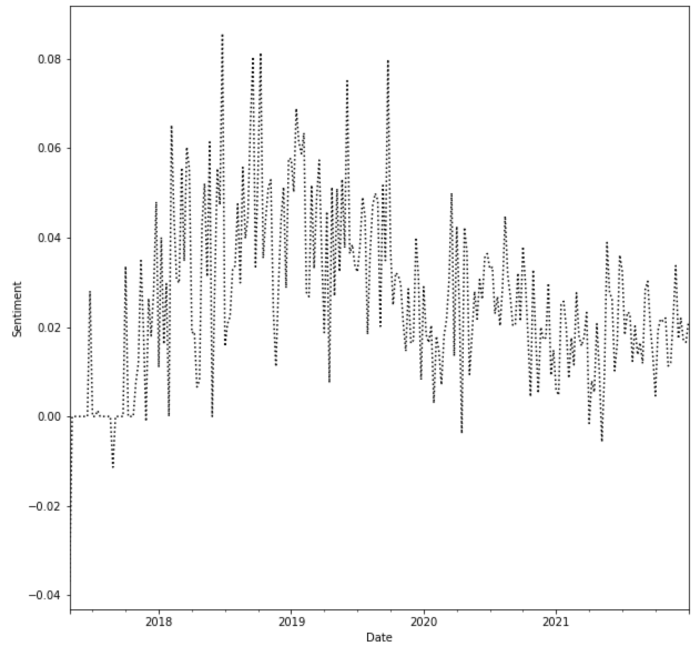
Panel A. Number of Technical News Articles



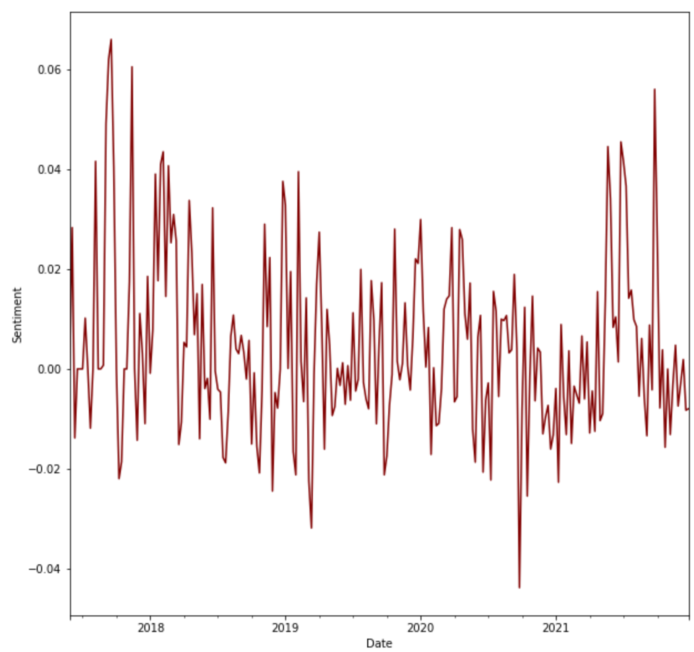
Panel B. Number of Fundamental News Articles

This graph shows the Technical Sentiment Index (Panel A) and the Fundamental Sentiment Index (Panel B). The data is weekly between June 2017 and December 2021.

Figure 5. Technical Sentiment Index and Fundamental Sentiment Index



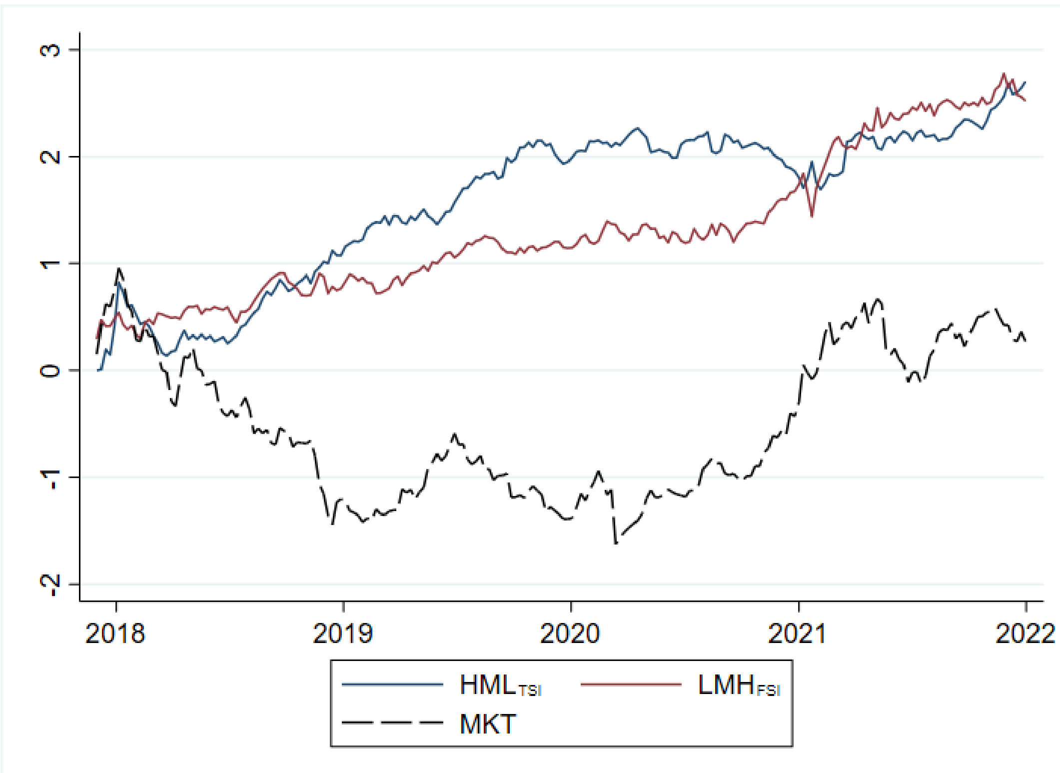
Panel A. Technical Sentiment Index



Panel B. Fundamental Sentiment Index

This graph shows the Technical Sentiment Index (Panel A) and the Fundamental Sentiment Index (Panel B). The data is weekly between June 2017 and December 2021.

Figure 6. Cumulative returns of Technical Sentiment Index and Fundamental Sentiment Index Strategy



This graph shows the cumulative returns of the Technical Sentiment Index (HML_{TSI}), Fundamental Sentiment Index (LMH_{FSI}), and market portfolio (MKT). The data is weekly between June 2017 and December 2021.

Figure 7. TSI and FSI Portfolio Turnover

The figure shows cryptocurrency turnover for low beta TSI portfolios (Panel A), high beta TSI portfolios (Panel B), low beta FSI portfolios (Panel C), and high beta FSI portfolios (Panel D). The data are between June 2017 and December 2021.

Table 1. Summary Statistics and Correlations with Existing Cryptocurrency Risk Factors

This table reports summary statistics of the Technical Sentiment Index (TSI), Fundamental Sentiment Index (FSI) in Panel A. Correlations between portfolio ranking of Technical Sentiment Index (TSI), Fundamental Sentiment Index (FSI), and size factor, momentum factor, liquidity factor, and volatility factor are reported in Panel B. p-values are reported in brackets. ** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Weekly data are between June 2017 and December 2020.

*P*anel A: Summary Statistics of TSI and FSI

	Mean	SD	Min	Max	Skewness	Kurtosis	Dickey-Fuller t-statistics
TSI	0.027	0.019	-0.011	0.086	0.570	3.162	-3.930***
FSI	0.004	0.018	-0.044	0.066	0.849	4.021	-7.344***

*P*anel B: Correlation

Variables	TSI	FSI	Size factor	Momentumfactor	Volatility factor	Liquidity factor
TSI	1.00					
FSI	0.04	1.00				
	(0.00)					
Size factor	-0.04	-0.12	1.00			
	(0.00)	(0.00)				
Momentum factor	0.01	-0.06	0.11	1.00		
	(0.41)	(0.00)	(0.00)			
Volatility factor	0.08	-0.04	-0.29	0.19	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)		
Liquidity factor	0.06	0.07	-0.64	-0.08	0.31	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 2. Portfolios sorted on Technical and Fundamental Sentiment Index

This table reports summary statistics for the excess returns of 4 cryptocurrencies portfolios sorted on exposure to the Technical Sentiment Index β^{TSI} (Panel A) and Fundamental Sentiment Index β^{FSI} (Panel B). Portfolio 1 (P_1) contains cryptocurrencies with the lowest β^{TSI} (or β^{FSI}), and Portfolio 4 (P_4) contains cryptocurrencies with the highest β^{TSI} (or β^{FSI}). HML represents the portfolio that has a long position in the high beta portfolio (P_4) and a short position in the low beta portfolio (P_1), and LMH represents the portfolio that has a short position in the high beta portfolio (P_4) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std), skewness, kurtosis, and Sharpe ratios (SR). The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	HML_{TSI}
Mean	-0.28	0.08	0.20	0.37	0.66
					[2.54]
Std	0.97	0.94	0.95	1.02	0.51
Skewness	-0.56	-0.56	-0.60	-0.38	-1.12
Kurtosis	5.58	5.37	5.97	4.83	8.73
β	-1.64	-0.34	0.40	1.78	3.42
SR					1.30
Panel B: Fundamental Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	LMH_{FSI}
Mean	0.44	0.16	-0.13	-0.18	0.61
					[2.54]
Std	0.97	1.00	0.96	0.95	0.50
Skewness	-0.45	-0.19	-0.72	-0.74	0.22
Kurtosis	5.00	5.52	5.37	4.97	4.92
β	-1.36	-0.27	0.33	1.40	-2.76
SR					1.22

Table 3. Technical and Fundamental Sentiment Sorted Portfolio Profit and other Risk factors

This table reports contemporaneous time-series regressions of HML_{TSI} portfolio (Panel A) and LMH_{FSI} on the market factor, size factor, momentum factor, liquidity factor, and volatility factor. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are weekly from June 2017 and December 2021.

Panel A: HML_{TSI}					
	(1)	(2)	(3)	(4)	(5)
Constant	0.013***	0.010**	0.010**	0.010**	0.011**
	(2.55)	(2.13)	(2.14)	(2.19)	(2.12)
Market factor$_t$	0.036	0.044	0.045	0.039	0.040
	(0.50)	(0.63)	(0.63)	(0.58)	(0.59)
Size factor$_t$		0.192*	0.197**	0.223**	0.233**
		(1.91)	(2.01)	(2.15)	(2.16)
Momentum factor$_t$			-0.027	-0.021	-0.022
			(-0.22)	(-0.17)	(-0.19)
Liquidity factor$_t$				0.248	0.227
				(1.16)	(1.06)
Volatility factor$_t$					0.094
					(0.51)
Observations	214	214	214	214	214
R^2	0.003	0.037	0.038	0.047	0.050

Panel B: LMH_{FSI}					
	(1)	(2)	(3)	(4)	(5)
Constant	0.012***	0.014***	0.013***	0.014***	0.013***
	(2.58)	(3.24)	(3.24)	(3.28)	(3.22)
Market factor$_t$	0.077	0.070	0.076	0.067	0.066
	(1.64)	(1.47)	(1.58)	(1.44)	(1.44)
Size factor$_t$		-0.169*	-0.128	-0.085	-0.093
		(-1.70)	(-1.37)	(-0.93)	(-1.12)
Momentum factor$_t$			-0.222***	-0.212**	-0.211**
			(-2.73)	(-2.57)	(-2.53)
Liquidity factor$_t$				0.401**	0.417**
				(2.02)	(2.08)
Volatility factor$_t$					-0.072
					(-0.43)
Observations	214	214	214	214	214
R^2	0.015	0.042	0.119	0.145	0.146

Table 4. Technical and Fundamental Sentiment Sorted Portfolio Profit and Value Risk factors

This table reports contemporaneous time-series regressions of HML_{TSI} portfolio (Panel A) and LMH_{FSI} on Value factors as in Cong et al. (2021). t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are weekly from June 2017 and December 2021.

Panel A: HML_{TSI}			
	(1)	(2)	(3)
Value factor (T/M ratio)	0.210*		
	(1.71)		
Value factor (U/M ratio)		0.214**	
		(2.24)	
Value factor (A/M ratio)			0.217**
			(2.27)
Constant	0.011***	0.010**	0.011***
	(2.58)	(2.33)	(2.53)
Observations	214	214	214
R^2	0.07	0.08	0.09

Panel B: LMH_{FSI}			
	(1)	(2)	(3)
Value factor (T/M ratio)	0.256***		
	(3.51)		
Value factor (U/M ratio)		0.238***	
		(3.55)	
Value factor (A/M ratio)			0.207***
			(2.98)
Constant	0.010***	0.009**	0.010**
	(2.45)	(1.98)	(2.30)
Observations	214	214	214
R^2	0.10	0.11	0.08

Table 5. Cross-Sectional regressions

This table reports Fama Macbeth cross-sectional regressions for Technical Sentiment Index betas β^{TSI} (Panel A), and Fundamental Sentiment Index betas β^{FSI} (Panel B). We run the model below:

$$rx_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}_{i,t}^{SI} + \lambda_{2,t}X_{i,t} + \epsilon_{i,t+1}$$

where $rx_{i,t+1}$ is the individual cryptocurrency return, SI is TSI for Panel A and FSI in Panel B. We report t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index betas β^{TSI}						
	(1)	(2)	(3)	(4)	(5)	(6)
β_t^{TSI}	0.005***	0.005***	0.005***	0.006***	0.006***	0.006***
	(3.43)	(3.52)	(3.47)	(3.75)	(3.61)	(3.55)
β_t^{MKT}		-0.004	-0.004	-0.003	-0.008	-0.006
		(-0.57)	(-0.52)	(-0.41)	(-0.97)	(-0.82)
$Size_t$			-0.001	-0.001	-0.002*	-0.001
			(-1.41)	(-1.27)	(-1.66)	(-1.20)
$Momentum_t$				0.006	0.006	0.011
				(0.69)	(0.67)	(1.02)
$Liquidity_t$					0.210	0.241
					(1.05)	(1.22)
$Volatility_t$						-0.150
						(-0.95)
Constant	0.002	0.006	0.035	0.030	0.044*	0.045
	(0.20)	(0.53)	(1.42)	(1.25)	(1.73)	(1.40)
Observations	6,138	6,138	6,138	6,138	6,138	6,138
R^2	0.06	0.11	0.15	0.23	0.29	0.34

Panel B: Fundamental Sentiment Index betas β^{FSI}						
	(1)	(2)	(3)	(4)	(5)	(6)
β_t^{FSI}	-0.004***	-0.004**	-0.004***	-0.005**	-0.005**	-0.005**
	(-2.61)	(-2.45)	(-2.65)	(-2.23)	(-2.28)	(-2.00)
β_t^{MKT}		-0.005	-0.005	-0.002	-0.007	-0.006
		(-0.63)	(-0.66)	(-0.30)	(-0.80)	(-0.73)
$Size_t$			-0.002*	-0.002	-0.002*	-0.002*
			(-1.69)	(-1.60)	(-1.79)	(-1.71)
$Momentum_t$				0.002	0.002	0.006
				(0.15)	(0.23)	(0.51)
$Liquidity_t$					0.228	0.263
					(1.10)	(1.23)
$Volatility_t$						-0.156
						(-1.13)
Constant	0.001	0.006	0.043*	0.040	0.048*	0.056**
	(0.12)	(0.56)	(1.73)	(1.61)	(1.94)	(2.02)
Observations	6,138	6,138	6,138	6,138	6,138	6,138
R^2	0.05	0.11	0.15	0.23	0.30	0.35

Table 6. Long-term predictive power of Technical Sentiment Index and Fundamental Sentiment Index

This table reports Fama Macbeth cross-sectional regressions for Technical Sentiment Index betas β^{TSI} (Panel A), and Fundamental Sentiment Index betas β^{FSI} (Panel B). We run the model below:

$$rx_{i,t+n} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}^{SI}_{i,t} + \lambda_{2,t}X_{i,t} + \epsilon_{i,t+1}$$

where $rx_{i,t+n}$ is the individual cryptocurrency return n weeks ahead, SI is TSI for Panel A and FSI in Panel B. t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index betas β^{TSI}												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	n = 1	n = 2	n = 3	n =4	n = 5	n = 6	n = 7	n = 8	n = 9	n = 10	n = 11	n = 12
β^{TSI}_t	0.006***	0.007***	0.007***	0.007***	0.006***	0.006***	0.007***	0.007***	0.007***	0.007***	0.005***	0.004**
	(3.55)	(3.93)	(3.61)	(4.48)	(3.53)	(3.90)	(4.06)	(4.20)	(4.23)	(3.68)	(2.66)	(2.38)
β^{MKT}_t	-0.006	-0.009	-0.010	-0.004	0.000	0.001	-0.002	-0.001	-0.008	-0.010	-0.008	-0.006
	(-0.82)	(-1.05)	(-1.32)	(-0.57)	(0.05)	(0.06)	(-0.27)	(-0.10)	(-1.03)	(-1.34)	(-1.08)	(-0.78)
$Size_t$	-0.001	-0.002	-0.003*	-0.003*	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002	-0.001	-0.000
	(-1.20)	(-1.38)	(-2.21)	(-2.58)	(-1.92)	(-1.72)	(-1.78)	(-1.62)	(-1.00)	(-1.24)	(-0.79)	(-0.42)
$Momentum_t$	0.011	-0.002	-0.015	-0.009	-0.017	-0.004	0.003	0.020*	0.013	0.005	0.011	-0.002
	(1.02)	(-0.21)	(-1.29)	(-0.80)	(-1.45)	(-0.49)	(0.36)	(2.15)	(1.27)	(0.56)	(1.11)	(-0.27)
$Liquidity_t$	0.004	-0.002	-0.006	-0.005	-0.005	-0.006	-0.004	-0.006	-0.009*	-0.008	-0.005	-0.003
	(1.22)	(0.20)	(-0.98)	(0.34)	(0.89)	(0.77)	(0.62)	(-0.72)	(0.76)	(1.17)	(1.69)	(0.46)
$Volatility_t$	-0.150	-0.174	-0.195	-0.273*	-0.187	-0.322*	-0.337*	-0.325*	-0.188	-0.115	-0.069	0.134
	(-0.95)	(-1.35)	(-1.47)	(-2.03)	(-1.17)	(-2.54)	(-2.59)	(-2.43)	(-1.20)	(-0.70)	(-0.43)	(0.92)
Constant	0.045	0.056	0.081*	0.082**	0.059	0.053	0.056	0.048	0.041	0.047	0.031	0.015
	(1.40)	(1.43)	(2.23)	(2.71)	(1.97)	(1.65)	(1.85)	(1.54)	(1.19)	(1.31)	(0.94)	(0.49)
Observations	5,911	5,869	5,827	5,786	5,744	5,703	5,661	5,619	5,578	5,537	5,496	5,455
R^2	0.34	0.34	0.32	0.31	0.31	0.32	0.33	0.32	0.33	0.33	0.34	0.33
Panel B: Fundamental Sentiment Index betas β^{FSI}												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	n = 1	n = 2	n = 3	n =4	n = 5	n = 6	n = 7	n = 8	n = 9	n = 10	n = 11	n = 12
β^{FSI}_t	-0.005**	-0.004**	-0.003*	-0.003*	-0.004**	-0.003	-0.004*	-0.004***	-0.004***	-0.004*	-0.003	-0.001
	(-2.00)	(-2.16)	(-1.80)	(-1.92)	(-2.54)	(-1.61)	(-2.32)	(-2.61)	(-2.53)	(-1.97)	(-1.54)	(-0.76)
β^{MKT}_t	-0.006	-0.008	-0.003	-0.003	-0.000	-0.000	0.000	-0.002	-0.006	-0.011	-0.010	-0.006
	(-0.73)	(-0.92)	(-0.39)	(-0.36)	(-0.01)	(-0.02)	(0.06)	(-0.26)	(-0.86)	(-1.53)	(-1.27)	(-0.86)
$Size_t$	-0.002	-0.002	-0.002	-0.003*	-0.003*	-0.003*	-0.003*	-0.003*	-0.002	-0.002	-0.001	-0.001
	(-1.71)	(-1.76)	(-1.73)	(-2.53)	(-2.21)	(-2.14)	(-2.58)	(-2.42)	(-1.53)	(-1.44)	(-0.94)	(-0.66)
$Momentum_t$	0.006	-0.006	-0.012	-0.004	-0.014	0.002	0.011	0.028**	0.017	0.007	0.011	-0.007
	(0.51)	(-0.51)	(-1.03)	(-0.34)	(-1.28)	(0.19)	(1.19)	(2.95)	(1.59)	(0.72)	(1.17)	(-0.74)
$Liquidity_t$	0.263	0.458	-0.883	0.807	0.104	0.532	0.713	-0.788	0.914	0.218	0.154	0.567
	(1.23)	(0.56)	(-0.70)	(0.67)	(1.10)	(0.47)	(0.72)	(-0.64)	(0.69)	(1.37)	(1.84)	(0.75)
$Volatility_t$	-0.156	-0.172	-0.149	-0.253	-0.224	-0.323*	-0.399**	-0.383**	-0.252	-0.119	-0.0890	0.153
	(-1.13)	(-1.29)	(-0.96)	(-1.89)	(-1.49)	(-2.29)	(-2.77)	(-2.69)	(-1.57)	(-0.73)	(-0.56)	(0.97)
Constant	0.056*	0.056	0.050	0.075*	0.067*	0.065*	0.074*	0.070*	0.058	0.053	0.038	0.022
	(2.01)	(1.83)	(1.75)	(2.51)	(2.22)	(2.03)	(2.54)	(2.41)	(1.76)	(1.62)	(1.23)	(0.72)
Observations	5,911	5,869	5,827	5,786	5,744	5,703	5,661	5,619	5,578	5,537	5,496	5,455
R^2	0.35	0.34	0.31	0.31	0.31	0.32	0.32	0.33	0.34	0.33	0.34	0.32

Table 7. Asset Pricing Tests

This table reports regressions results for the two-factor model, including the MKT and TSI (Panel A) or FSI (Panel B) risk factors. Test assets used are 4 TSI portfolios (Panel A), or 4 FSI (Panel B) portfolios. Portfolios are rebalanced weekly. Newey and West (1987) t-statistics and Shanken (1992) (SH) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. We also report R^2, Root Mean Squared Error (RMSE). The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index				
	λ_{MKT}	λ_{TSI}	RMSE	R^2
FMB	-0.043	0.012***	0.0005	0.99
(NW)	[-0.73]	[2.52]		
(SH)	[-0.78]	[2.65]		

Panel B: Fundamental Sentiment Index				
	λ_{MKT}	λ_{FSI}	RMSE	R^2
FMB	-0.032	-0.012***	0.0018	0.86
(NW)	[-0.49]	[-3.03]		
(SH)	[-0.60]	[-2.57]		

Table 8. Adding Technical and Fundamental to existing asset pricing models

This table reports regressions results for the asset pricing tests. Test assets used are four size portfolios, four momentum portfolios, four liquidity portfolios, four volatility portfolios, four TSI portfolios, and four FSI portfolios. Portfolios are rebalanced weekly. Newey and West (1987) (NW) and Shanken (1992) (SH) t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. We also report R^2, Root Mean Squared Error (RMSE). The data are weekly from June 2017 and December 2021.

Panel A: One-factor model

	λ_{MKT}	RMSE	R^2
FMB	-0.002	0.004	0.049
(NW)	[-0.25]		
(SH)	[-0.20]		

	λ_{MKT}	λ_{TSI}	λ_{FSI}	RMSE	R^2
FMB	-0.002	0.013**	-0.009*	0.003	0.43
(NW)	[-0.22]	[2.14]	[-1.74]		
(SH)	[-0.17]	[2.18]	[-1.40]		

Panel B: Two-factor model

	λ_{MKT}	λ_{Size}	RMSE	R^2
FMB	-0.004	0.011*	0.003	0.27
(NW)	[-0.55]	[1.87]		
(SH)	[-0.41]	[1.77]		

	λ_{MKT}	λ_{Size}	λ_{TSI}	λ_{FSI}	RMSE	R^2
FMB	-0.004	0.013***	0.01**	-0.012**	0.002	0.67
(NW)	[-0.49]	[2.42]	[1.96]	[-2.31]		
(SH)	[-0.40]	[2.41]	[1.75]	[-1.79]		

Panel C: Three-factor model

	λ_{MKT}	λ_{Size}	λ_{MOM}	RMSE	R^2
FMB	-0.003	0.013*	-0.025***	0.003	0.46
(NW)	[-0.47]	[2.04]	[-2.52]		
(SH)	[-0.36]	[1.98]	[-1.89]		

	λ_{MKT}	λ_{Size}	λ_{MOM}	λ_{TSI}	λ_{FSI}	RMSE	R^2
FMB	-0.004**	0.013***	-0.011	0.01**	-0.012**	0.002	0.68
(NW)	[-0.46]	[2.42]	[-0.85]	[1.96]	[-2.28]		
(SH)	[-0.38]	[2.40]	[-0.66]	[1.76]	[-1.77]		

Panel D: Five-factor model

	λ_{MKT}	λ_{Size}	λ_{MOM}	$\lambda_{Liquidity}$	$\lambda_{Volatility}$	RMSE	R^2
FMB	-0.003	0.013**	-0.024*	-0.001	-0.003	0.003	0.46
(NW)	[-0.35]	[2.09]	[-1.91]	[-0.21]	[-1.13]		
(SH)	[-0.31]	[2.00]	[-1.85]	[-0.19]	[-1.01]		

	λ_{MKT}	λ_{Size}	λ_{MOM}	$\lambda_{Liquidity}$	$\lambda_{Volatility}$	λ_{TSI}	λ_{FSI}	RMSE	R^2
FMB	-0.004**	0.012***	-0.013	-0.004	-0.004	0.012**	-0.011**	0.002	0.73
(NW)	[-0.49]	[2.45]	[-0.96]	[-1.13]	[-1.33]	[2.27]	[-2.20]		
(SH)	[-0.47]	[2.40]	[-0.81]	[-0.88]	[-1.25]	[2.00]	[-1.70]		

Table 9. Portfolios sorted on Technical and Fundamental Sentiment Index (Top 15 cryptocurrencies by market capitalization)

This table reports summary statistics for the excess returns of three currency portfolios sorted on exposure to the Technical Sentiment Index TSI (Panel A) and Fundamental Sentiment Index FSI (Panel B) for the top 15 cryptocurrencies by market capitalization. Portfolio 1 (P_1) contains currencies with the lowest Fundamental Sentiment Index betas, and Portfolio 3 (P_3) contains currencies with the highest Fundamental Sentiment Index betas. HML represents the portfolios that have a short position in the high beta portfolio (P_3) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std), and Sharpe ratios (SR).The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index Portfolio				
	P_1	P_2	P_3	HML
Mean	0.10	0.23	0.75	0.65
				[2.11]
Std	1.02	1.02	1.11	0.62
β				
SR				1.04
Panel B: Fundamental Sentiment Index Portfolio				
	P_1	P_2	P_3	LMH
Mean	0.64	0.37	-0.04	0.68
				[2.00]
Std	1.12	1.12	0.89	0.69
SR				0.69

Table 10. Placebo: Portfolios sorted on other Topics

This table reports summary statistics for the excess returns of four portfolios sorted on exposure to Lending (Panel A), Regulation (Panel B), Payments (Panel C), Derivatives (Panel D), Social Media (Panel E), and Hedging (Panel F). Portfolio 1 (P_1) contains currencies with the lowest betas, and Portfolio 4 (P_4) contains currencies with the highest betas. HML represents the portfolio that has a short position in the high beta portfolio (P_4) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std), and Sharpe ratios (SR). The data are weekly from June 2017 and December 2021.

Panel A: Lending Sentiment Portfolio						Panel B: Regulation Sentiment Portfolio					
	P_1	P_2	P_3	P_4	HML		P_1	P_2	P_3	P_4	HML
Mean	0.15	0.05	0.27	0.10	0.05	Mean	0.20	0.13	0.33	-0.13	0.33
					[0.19]						[1.20]
Std	0.46	0.43	0.47	0.50	0.23	Std	0.49	0.44	0.48	0.48	0.27
SR					0.23	SR					1.21

Panel C: Payment Sentiment Portfolio						Panel D: Derivatives Sentiment Portfolio					
	P_1	P_2	P_3	P_4	HML		P_1	P_2	P_3	P_4	HML
Mean	0.20	0.40	-0.07	-0.02	0.23	Mean	0.25	0.30	-0.07	0.02	0.23
					[1.00]						[0.93]
Std	0.46	0.49	0.45	0.46	0.22	Std	0.46	0.47	0.47	0.47	0.23
SR					1.05	SR					1.00

Panel E: Social Media Sentiment Portfolio						Panel F: Hedging Sentiment Portfolio					
	P_1	P_2	P_3	P_4	HML		P_1	P_2	P_3	P_4	HML
Mean	0.26	0.14	0.25	-0.11	0.37	Mean	0.20	0.24	-0.10	0.19	0.02
					[1.15]						[0.07]
Std	0.47	0.45	0.49	0.46	0.26	Std	0.47	0.46	0.45	0.49	0.24
SR					1.44	SR					0.08

Internet Appendix to

"Fundamental vs. Technical Analysis: News-Based Factors and Cryptocurrency Risk Premia"

by

Ilias Filippou   My T. Nguyen   Ganesh Viswanath-Natraj

(Not for publication)

Appendix A: Examples of Technical Analysis Articles

1.1 Sample of Technical Articles

Some articles identified as Technical articles are listed.

Technical Article 1

"*02:39 * For more technical analyses, click SINGAPORE, Jan 11 (Reuters) - Bitcoin may gain more to a resistance at $15,254, a break above which could lead to a further gain to $16,011. For a chart: http://tmsnrt.rs/2Dh0MSn The resistance is provided by the 38.2 percent retracement of the uptrend from the Dec. 30, 2017 low of $12,050 to the Jan. 6 high of $17,235. The strong recovery of the price from the Jan. 10 low of $13,412 signals a completion of the correction from $17,235. The bullish divergence on the hourly MACD confirms the reversal of the downtrend. Bitcoin may drop a bit further to a support at $14,031 before rising again. The drop is regarded as a pullback towards a falling trendline. A break below $14,031 could cause a loss to $13,274. *Use EIKON news "Alerts" to get reports sent to your email box automatically. For guidance, click http://tmsnrt.rs/29exTKN ** Wang Tao is a Reuters market analyst for commodities and energy technicals. The views expressed are his own.*"

Technical Article 2

"*After a drop yesterday, bitcoin (BTC) risks another move below $6,000 in the next 24 hours, but it will still likely fare better than other cryptocurrencies. On Tuesday, bitcoin closed (as per UTC) below the immediate support of $6,108 (June 13 low), pouring cold water over the prospects of a corrective rally above a major technical hurdle at $6,425 (April 1 low). The failure to capitalize on early signs of short-term bullish reversal has shifted risk in favor of a break below the $6,000 mark (February low). Even if a drop in prices is seen, bitcoin could still outperform other cryptocurrencies, as a break below $6,000 could trigger risk aversion in the markets, forcing investors to venture out of high-risk alternative cryptocurrencies and into bitcoin. At press time, BTC is trading at $6,100 on Bitfinex Ã¢â‚¬â€œ down 2.25 percent on* *a 24-hour basis. Daily chart Click to view image BTC was expected to scale April 1 low of 6,425 this week, courtesy of the bullish price-relative strength index (RSI) and bullish price-money flow index (MFI) divergence and the long-legged doji . Instead, it created another lower high (bearish pattern) on the chart as it fell from $6,341 (June 25 high) to $6,020 (today's low). Further, BTC closed (as per UTC) below the immediate support of $6,108 (June 13 low) yesterday, putting the focus back on the broader bearish outlook, as indicated by the falling channel and downward sloping Bollinger Bands (+2,-2 standard deviation on the 20-day moving average). So, BTC could drop below $6,000 in the next 24 hours. On the downside, immediate support is lined up at $5,755 (Sunday's doji candle low) and $5,717 (lower Bollinger Band). Should prices take a positive turn, immediate resistance is located at $6,341 (June 25 high) and $6,560 (20-day MA). Risk aversion Clearly, BTC chart is biased to the bears, however, other cryptocurrencies will likely post bigger losses, as indicated by a bearish breakdown in ether-bitcoin (ETH/BTC) exchange rate. The fiat money tends to flow into cryptocurrency markets via major assets like BTC and is then rotated into alternative cryptocurrencies once the bitcoin valuations look overstretched. Further, the rotation of money from bitcoin and into alternative cryptocurrencies is usually a sign the investors are eager to take more risk (a "risk-on" market). On the contrary, rotation of money out of alternative cryptocurrencies and into major assets like BTC happens when investors turn risk-averse ("risk-off" market). As most alternative cryptocurrencies are built on the ethereum blockchain, the ETH/BTC serves as a good indicator of risk-on/risk-off sentiment, i.e. rising ETH/BTC means risk-on and falling ETH/BTC means risk-off. Accordingly, the bearish breakdown seen in the chart below indicates that risk aversion will likely increase in the short-run and the alternative cryptocurrencies will post bigger drops than bitcoin. ETH/BTC daily chart Click to view image The above chart (prices as per Bittrex) shows a bearish Bollinger Band breakdown and a downside break of the trading range. So, ETH/BTC could be heading lower towards 0.0655BTC (Aug. 15, 2017 low)."*

Technical Article 3

*"Ethereum price declined heavily from the $163.50 swing high and traded below $140.00. ETH/USD is currently holding the $125.00 support, but buyers seem to be struggling. **

*Ethereum price is facing a lot of hurdles near the $134.00 and $144.00 resistances. * ETH/USD is following a short term declining channel with resistance near $134.00 on the 30-minute chart. * The price may decline further if buyers fail to defend the $124.00 and $120.00 support levels. Ethereum ETH Price Ethereum Price Analysis This past week, we saw a solid upward move above the $150.00 barrier in Ethereum price. The price even cleared the $160.00 resistance and formed a new monthly high at $163.50. Click to view image Click to Enlarge Chart Looking at the 30-minute chart of ETH/USD, the pair started a major downside move from the $163.50 high. Sellers took control and pushed the price below the $155.00, $150.00 and $142.00 support levels. There was even a close below the $140.00 support and the 25 simple moving average (30-min). The price traded as low as $124.50 and later started trading in a range. There was a short term correction above the $138.00 and $140.00 levels. Buyers pushed the price above the 23.6% Fib retracement level of the recent decline from the $163.50 high to $124.41 low. However, they struggled to gain pace above the $140.00 resistance and the 25 SMA. Besides, there was no proper test of the 50% Fib retracement level of the recent decline from the $163.50 high to $124.41 low. ETH/USD traded as high as $141.65 recently and later declined below $140.00 and $138.00. At the moment, the price is following a short term declining channel with resistance near $134.00 on the same chart. If the price breaks the channel resistance, there is a chance of an upward move towards the $140.00 and $144.00 resistance levels. On the other hand, a downside break below the $124.50 low in Ethereum price may clear the path for more losses. The next key support is at $118.00, below which ETH could tumble and test the $100.00 support area. The market data is provided by TradingView, Bitfinex.*"

1.2 Sample of Technical Sentences and Their Sentiment Score

Some sentences in Technical articles with their sentiment score are listed

Technical Sentence 1

"*monday, feb. 19: the bitcoin price has surpassed $11,000 twice since sunday as bullish sentiment returns to markets and new support begins to form.*" (Sentiment Score -0.1)

Technical Sentence 2

"*but he said he feels particularly confident about his bullish call on bitcoin now.*" (Sentiment Score -0.17)

Technical Sentence 3

"*the falling channel and downward sloping bollinger bands (standard deviation of +2, -2 on 20-day moving average) indicate that the bear grip on bitcoin is still intact.*" (Sentiment Score 0.14)

Technical Sentence 4

"*ripple's xrp technical analysis: xrp/usd bears are further pressing for devastating support breakout * ripple's xrp price on friday is trading marginally in the red, down some 0.70%.*" (Sentiment Score 0.14)

Technical Sentence 5

"*the ada/usd pair has formed an inside day candlestick pattern today, which suggests indecision among the bulls and the bears.*" (Sentiment Score 0)

Appendix B: Examples of Fundamental Analysis Articles

2.1 Sample of Fundamental Articles

Some articles identified as Fundamental articles are listed

Fundamental Article 1

"*Cryptocurrencies have been a winning bet this year, but the chip makers who play a key role in the market are still playing their hands very cautiously. The exploding value of cryptocurrencies this year has created a strong incentive for "miners" who use high-end computers that match and update cryptocurrency transactions in return for rewards. Mining for many of the fastest-rising currencies, including ethereum, is powered by graphics processors from companies like Nvidia and Advanced Micro Devices. These chips, also called GPUs, are the same type used in high-end gaming PCs. Cryptocurrency mining seems to have created a decent market for both companies. Nvidia credits about $220 million in revenue over its last two quarters to cryptocurrency demand, which is a little less than 5% of the company's total sales. AMD CEO Lisa Su estimates the market will account for a mid-single digit percentage of the company's projected 23% growth this year, which suggests revenue around $50 million for the year. But neither company wants to bake cryptocurrency into their outlooks, and with good reason. Cryptocurrencies are highly volatile. Changes to the underlying technology can sharply affect the economic value of mining. Joseph Moore of Morgan Stanley says an expected shift by ethereum in the next year or so will render GPU-based mining for the currency "obsolete." Still, there were 26 cryptocurrencies with total market values over $1 billion as of Thursday. Only bitcoin and ethereum were in that range a year ago. Mitch Steves of RBC Capital notes that several of those rising fast are mined with GPUs. Cryptocurrencies may be unpredictable, but they are likely here to stay. Which is ultimately good news for those with chips in the game. Write to Dan Gallagher at dan.gallagher@wsj.com (END) Dow Jones Newswires*"

Fundamental Article 2

"The Bitcoin (BTC) hash rate reached a new all-time high today, according to data from monitoring resource Blockchain.com on July 7. The previous record was broken in the second half of June, when bitcoin hash rate reached 65.19 TH/s and growth has steadily continued since then. Hash rate is the number of calculations that a given hardware or network can perform every second. It is a very important parameter for miners, as a higher hash rate will increase their chances of solving the mathematical problem, sealing off the block and collecting their reward. A higher network hash rate also increases the amount of resources needed for performing a 51% attack, making the network safer."

Fundamental Article 3

"Aave, the DeFi platform, has announced that it will be implementing Polygon to offer more scalability and lower fees amid increasing congestion on the Ethereum Network. The platform was originally launched on Ethereum L1 and quickly became one of the most important Decentralized Finance (DeFi) projects during the DeFi Summer of 2020, a period in which DeFi took the cryptocurrency ecosystem by storm in what would become one of the biggest bull runs seen by the cryptocurrency market. However, despite Ethereum occupying the spot as the leading blockchain network at this time, the network has seen its block space supply grow increasingly scarce and limited, which has resulted in increased congestion and gas prices, which have affected the projects it initially helped succeed. Aave Sees Polygon as a Solution Now, Aave integration with Polygon will allow users to enjoy more scalability, faster transactions, and lower gas prices that will boost the platform to new levels as the cryptocurrency market continues to grow. The move is the "first wave in Aave Protocol. "New Frontiers exploration mission, which is aimed to allow it to build synergies with other projects and expand to a multi-market approach to secure the future growth of the protocol. Using Sidechains with Polygon This first wave will see the implementation of a scalable sidechain on Ethereum by using Polygon, increasing throughput and reducing fees, as well as allowing the collaboration with other DeFi protocols and projects by facilitating communication. Polygon partnership with Chainlink will also allow the Avee protocol to provide better quality on price feeds by taking advantage of one of the best Oracle Networks in the current cryptocurrency ecosystem, improving the protocol's current standards. Aave users will also have access to

MATIC, Polygon cryptocurrency, being able to use it as collateral in addition to other assets such as USDC, USDT, DAI, WETH, AAVE, and WBTC. Many Fresh Features This will be possible once the Smart Contract Bridge is deployed, with users who make use of it receiving part of transaction fees used in MATIC to cover part of their transaction fees on the Polygon blockchain. The bridge can also be used to transfer assets from Ethereum to Polygon, which will prove useful for users wanting to migrate their assets. The recent rise in popularity experienced by Polygon has also made the process of transferring assets to Polygon easier than ever before, with popular wallets like Metamask deploying one-click solutions. Transforming Ethereum Into a Multichain System Matic rebranded to Polygon earlier this year as it aimed to become a solution to Ethereum growing congestion problem by transforming it into a multi-chain network and offering integration with other Layer-2 solutions. With the rebranding, Polygon said it would extend the scope of the Matic Platform by allowing Ethereum to integrate scalation solutions like zkRollups, Optimistic Rollups, and Validium, as well as interchain communication protocols to become Ã¢â‚¬Å“the internet of blockchain. A Growing Platform Polygon, originally launched in 2019, has become increasingly relevant in the cryptocurrency ecosystem as the congestion on the Ethereum network increased. However, it would not be until early 2021 when the project would become one of the top 100 projects in the cryptocurrency market by market capitalization. The announcement of the integration saw MATICÃ value increase by over 10% in a matter of minutes, a similar trend to the one experienced by AAVE. Polygon also saw DeFi platform Zapper announced that it will be integrating the network, which is expected to be the first of many sidechains as xDAI, Optimism, and Binance Chain will also be covered in the future. These moves show an increasing interest from cryptocurrency projects to find alternatives to the Ethereum network at a time when its future is still uncertain as competition in the blockchain industry continues to increase. The post Aave Will Integrate With Polygon Sidechains for Much Lower Fees appeared first on Blockonomi."

2.2 Sample of Fundamental Sentences and Their Sentiment Score

Some sentences in Fundamental articles with their sentiment score are listed

Fundamental Sentence 1

"*the suspension appears to have plunged the bitcoin mining power as much as 30%.*" (Sentiment Score 0.2)

Fundamental Sentence 2

"*dr. sivakumar arumugam concluded,"the striking divergence between the global hash rate and bitcoin prices suggests that mining is becoming increasingly unprofitable, the review of publicly available data reveals that the global hash rate has been increasing at a steady exponential rate in recent months.*" (Sentiment Score 0.04)

Fundamental Sentence 3

"*coinhive reportedly had to shut down its services amidst a 50 percent decline in hash rate following the last monero hard fork.*" (Sentiment Score 0.19)

Fundamental Sentence 4

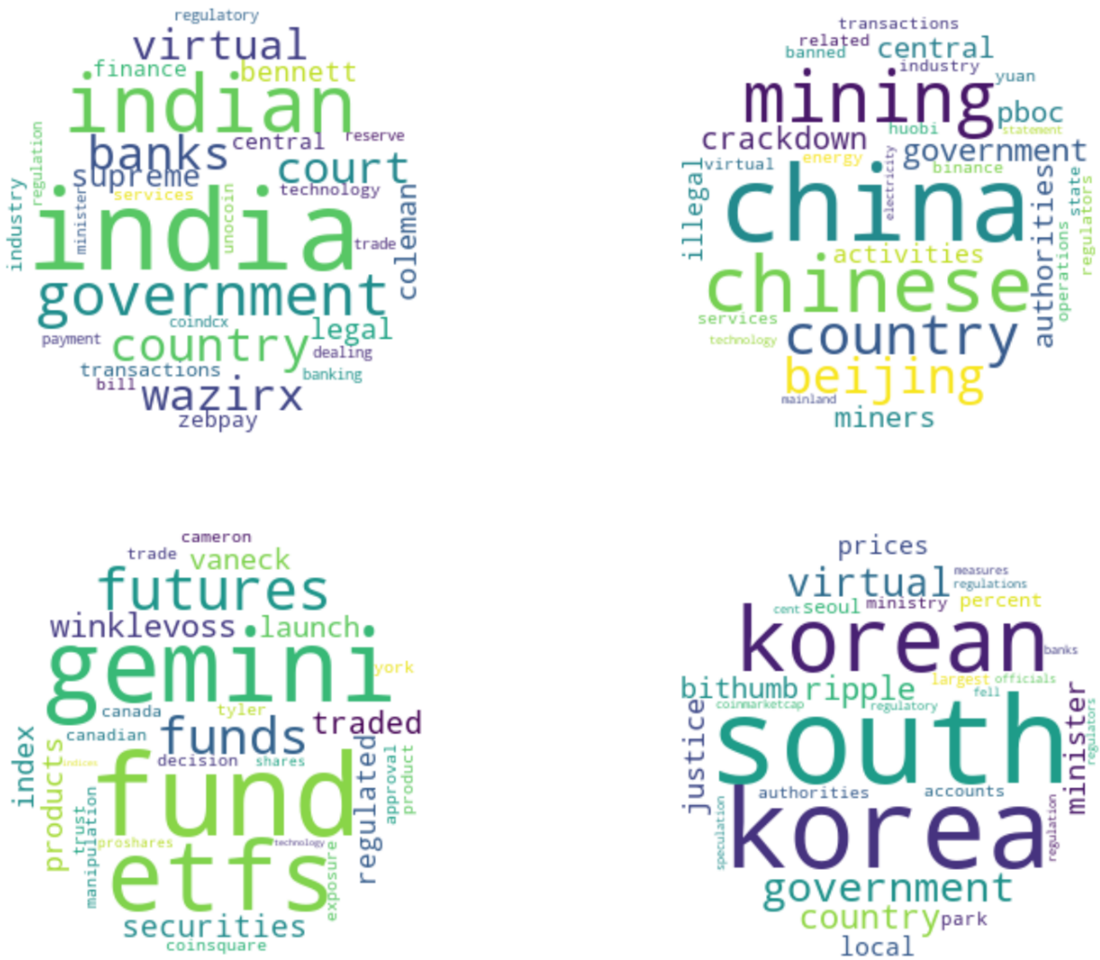
"*ethereum gas fees have exploded in 2021, which has been a hindrance to both inexpensive nfts, and also defi platforms that were designed to deal with small amounts of value.*" (Sentiment Score 0.09)

Fundamental Sentence 5

the scaling woes of ethereum are well-documented and came to a head when transaction costs soared in gas fees, and many dapps became prohibitively cumbersome to use and remain so today." (Sentiment Score 0.08)

Appendix C: Word Clusters of Alternative Topics

Figure A1. Regulation Topics generated from BERT topic modelling



The figure shows keywords for 4 Regulation topics. The data are between June 2017 and December 2021.

Figure A2. Lending Topic generated from BERT topic modeling

This graph shows keywords for the Lending topic. The data is weekly between June 2017 and December 2021.

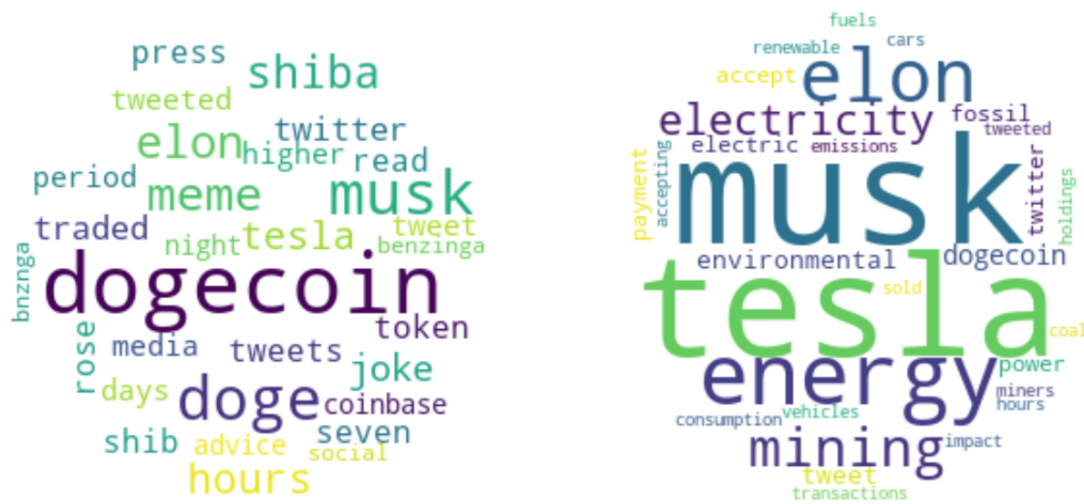
Figure A3. Payment Topic generated from BERT topic modeling

This graph shows keywords for the Payment topic. The data is weekly between June 2017 and December 2021.

Figure A4. Technical Derivatives Topics generated from BERT topic modelling

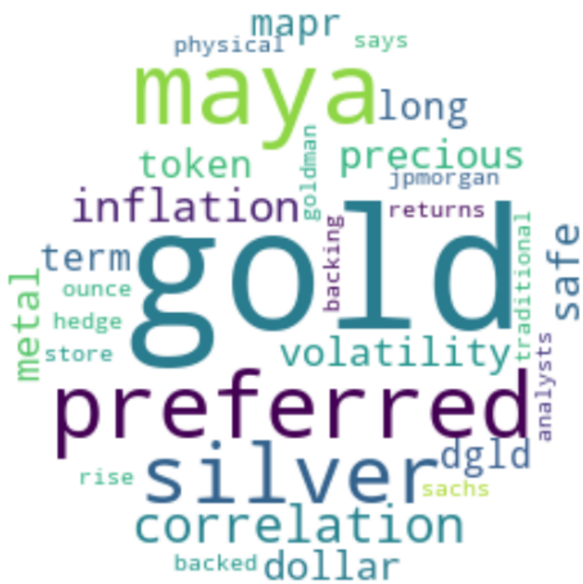
The figure shows keywords for 2 Technical Derivatives topics. The data are between June 2017 and December 2021.

Figure A5. Social Media Topics generated from BERT topic modeling



The figure shows keywords for 2 Social Media topics. The data are between June 2017 and December 2021.

Figure A6. Hedging Topic generated from BERT topic modeling



This graph shows keywords for the Hedging topic. The data is weekly between June 2017 and December 2021.

Appendix D: Additional Tables

Table A1. Summary Statistics of Full Sample

This table reports summary statistics of our cryptocurrency data per year. We present the number of cryptocurrencies, the total market capitalization at the end of the year (in Billion $), the ratio of the total market capitalization of our sample to the total market capitalization of the cryptocurrency market, the average volatility and the average number of accounts. Our sample contains weekly data from June 2017 to December 2021.

Full Sample					
Year	Number of coins	Total Market capitalization	Sample to total cryptocurrency market capitalization	volatility	Number of accounts
2017	20	661	0.87	0.91	73957.8
2018	25	145	0.78	0.91	64978.62
2019	30	195	0.83	0.91	58252.67
2020	40	654	0.91	0.91	58126.36
2021	43	1,750	0.82	0.91	71446.09

Table A2. Variable descriptions

This table reports descriptions of variables used in the paper.

Variable descriptions	
Variable	Description
MKT	Value-weighted returns of cryptocurrencies in the sample based on the market capitalization ratio.
Size	The difference between the average returns of the cryptocurrencies in the low portfolio (Small) by market capitalization and the average returns of the cryptocurrencies in the high portfolio (Big) by market capitalization.
Momentum	The difference between average returns of the cryptocurrencies in the high portfolio (Winner) by previous 6-week cumulative return and the average returns of the cryptocurrencies in the low portfolio (Loser) by previous 6-week cumulative return.
Liquidity	The difference between average returns of the cryptocurrencies in the high portfolio (Liquid) by Amihud ratio and the average returns of the cryptocurrencies in the low portfolio (Illiquid) by Amihud ratio.
Volatility	The difference between average returns of the cryptocurrencies in the high portfolio (High volatility) by idiosyncratic volatility and the average returns of the cryptocurrencies in the low portfolio (Low volatility) by idiosyncratic volatility.
Value (T/M ratio)	The difference between average returns of the cryptocurrencies in the high portfolio by transaction -to-market ratio and the average returns of the cryptocurrencies in the low portfolio by transaction -to-market ratio.
Value (U/M ratio)	The difference between average returns of the cryptocurrencies in the high portfolio by user -to-market ratio and the average returns of the cryptocurrencies in the low portfolio by user-to-market ratio.
Value (A/M ratio)	The difference between average returns of the cryptocurrencies in the high portfolio by address -to-market ratio and the average returns of the cryptocurrencies in the low portfolio by address to-market ratio.
Network 1 (BA growth)	The difference between average returns of the cryptocurrencies in the high portfolio by first difference of log values of total addresses with balance and the average returns of cryptocurrencies in the low portfolio by first difference of log values of total addresses with balance.
Network 2 (TA growth)	The difference between average returns of the cryptocurrencies in the high portfolio by first difference of log values of total addresses and the average returns of cryptocurrencies in the low portfolio by first difference of log values of total addresses.
Network 3 (Volgrowth)	The difference between average returns of the cryptocurrencies in the high portfolio by first difference of log values of total transaction volume on chain and the average returns of cryptocurrencies in the low portfolio by first difference of log values of total transaction volume on chain.
Network 4 (VolUSDgrowth)	The difference between average returns of the cryptocurrencies in the high portfolio by first difference of log values of total transaction volume on chain in USD and the average returns of cryptocurrencies in the low portfolio by first difference of log values of total transaction volume on chain in USD.

Table A3. Technical and Fundamental Sentiment Sorted Portfolio Profit and Network Risk factors

This table reports contemporaneous time-series regressions of HML_{TSI} portfolio (Panel A) and LMH_{FSI} on network factors as in Cong et al. (2021). t-statistics are reported in squared brackets, where *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data are weekly from June 2017 and December 2021.

	Panel A: HML_{TSI}			
	(1)	(2)	(3)	(4)
Network 1	-0.041 (-0.49)			
Network 2		0.147* (1.81)		
Network 3			0.058 (0.65)	
Network 4				0.107* (1.67)
Constant	0.012** (2.51)	0.013*** (2.62)	0.013** (2.54)	0.014*** (2.67)
Observations	214	214	214	214
R^2	0.00	0.03	0.00	0.01
	Panel B: LMH_{FSI}			
	(1)	(2)	(3)	(4)
Network 1	0.068 (0.77)			
Network 2		0.058 (0.81)		
Network 3			-0.024 (-0.24)	
Network 4				0.102 (1.10)
Constant	0.012*** (2.64)	0.012** (2.55)	0.012** (2.54)	0.013*** (2.90)
Observations	214	214	214	214
R^2	0.00	0.00	0.00	0.01

Table A4. Portfolios sorted on Technical and Fundamental Sentiment Index - First alternative proxy for sentiment

This table reports summary statistics for the excess returns of 4 cryptocurrencies portfolios sorted on exposure to the Technical Sentiment Index β^{TSI} (Panel A) and Fundamental Sentiment Index β^{FSI} (Panel B) based on the following specification to estimate sentiment:

$$Sent = \frac{\text{Number of negative words}}{\text{Total number of words}}$$

Portfolio 1 (P_1) contains cryptocurrencies with the lowest β^{TSI} (or β^{FSI}), and Portfolio 4 (P_4) contains cryptocurrencies with the highest β^{TSI} (or β^{FSI}). HML represents the portfolio that has a long position in the high beta portfolio (P_4) and a short position in the low beta portfolio (P_1), and LMH represents the portfolio that has a short position in the high beta portfolio (P_4) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std), skewness, kurtosis, and Sharpe ratios (SR). The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	HML_{TSI}
Mean	-0.18	0.14	0.16	0.25	0.44
					[2.02]
Std	0.14	0.13	0.14	0.13	0.07
SR					0.82
Panel B: Fundamental Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	LMH_{FSI}
Mean	0.38	0.23	-0.18	-0.13	0.51
					[2.16]
Std	0.14	0.14	0.13	0.13	0.07
SR					1.03

Table A5. Portfolios sorted on Technical and Fundamental Sentiment Index - Second alternative proxy for sentiment

This table reports summary statistics for the excess returns of 4 cryptocurrencies portfolios sorted on exposure to the Technical Sentiment Index β^{TSI} (Panel A) and Fundamental Sentiment Index β^{FSI} (Panel B) based on the following specification to estimate sentiment:

$$Sent = \frac{\text{Number of negative words-Number of positive words}}{\text{Number of negative words+Number of positive words}}$$

Portfolio 1 (P_1) contains cryptocurrencies with the lowest β^{TSI} (or β^{FSI}), and Portfolio 4 (P_4) contains cryptocurrencies with the highest β^{TSI} (or β^{FSI}). HML represents the portfolio that has a long position in the high beta portfolio (P_4) and a short position in the low beta portfolio (P_1), and LMH represents the portfolio that has a short position in the high beta portfolio (P_4) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std), skewness, kurtosis, and Sharpe ratios (SR). The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	HML_{TSI}
Mean	-0.37	0.27	0.05	0.44	0.81
					[3.29]
Std	0.13	0.13	0.13	0.15	0.07
SR					1.62
Panel B: Fundamental Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	LMH_{FSI}
Mean	0.40	0.14	-0.13	-0.11	0.51
					[2.07]
Std	0.14	0.14	0.13	0.13	0.07
SR					1.02

Table A6. Portfolios sorted on Technical and Fundamental Sentiment Index - First alternative specification to estimate β

This table reports summary statistics for the excess returns of 4 cryptocurrencies portfolios sorted on exposure to the Technical Sentiment Index β^{TSI} (Panel A) and Fundamental Sentiment Index β^{FSI} (Panel B) based on the following specification:

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{SI} SI + \beta_{i,t}^{MKT} MKT_t + \epsilon_{i,t}$$

Portfolio 1 (P_1) contains cryptocurrencies with the lowest β^{TSI} (or β^{FSI}), and Portfolio 4 (P_4) contains cryptocurrencies with the highest β^{TSI} (or β^{FSI}). HML represents the portfolio that has a long position in the high beta portfolio (P_4) and a short position in the low beta portfolio (P_1), and LMH represents the portfolio that has a short position in the high beta portfolio (P_4) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std), skewness, kurtosis, and Sharpe ratios (SR). The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	HML_{TSI}
Mean	-0.16	0.20	0.24	0.44	0.60
					[2.26]
Std	0.13	0.14	0.13	0.14	0.07
SR					1.11
Panel B: Fundamental Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	LMH_{FSI}
Mean	0.40	0.28	0.04	-0.09	0.49
					[2.05]
Std	0.14	0.13	0.13	0.14	0.08
SR					0.86

Table A7. Portfolios sorted on Technical and Fundamental Sentiment Index - Second alternative specification to estimate β

This table reports summary statistics for the excess returns of 4 cryptocurrencies portfolios sorted on exposure to the Technical Sentiment Index β^{TSI} (Panel A) and Fundamental Sentiment Index β^{FSI} (Panel B) based on the following specification.

$$rx_{i,t} = \alpha_{i,t} + \beta_{i,t}^{SI} SI + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{MOM} MOM_t \epsilon_{i,t}$$

Portfolio 1 (P_1) contains cryptocurrencies with the lowest β^{TSI} (or β^{FSI}), and Portfolio 4 (P_4) contains cryptocurrencies with the highest β^{TSI} (or β^{FSI}). HML represents the portfolio that has a long position in the high beta portfolio (P_4) and a short position in the low beta portfolio (P_1), and LMH represents the portfolio that has a short position in the high beta portfolio (P_4) and a long position in the low beta portfolio (P_1). For each portfolio, we report annualized mean and its t-statistics (reported in squared brackets), standard deviation (Std), skewness, kurtosis, and Sharpe ratios (SR). The data are weekly from June 2017 and December 2021.

Panel A: Technical Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	HML_{TSI}
Mean	-0.17	0.15	0.42	0.31	0.48
					[1.88]
Std	0.13	0.13	0.14	0.14	0.07
SR					0.91
Panel B: Fundamental Sentiment Index Portfolio					
	P_1	P_2	P_3	P_4	LMH_{FSI}
Mean	0.38	0.40	0.04	-0.18	0.55
					[2.19]
Std	0.14	0.14	0.13	0.13	0.08
SR					0.97