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REVIEW

Beyond pure hype: news sentiment and its role in the BTC and ETH futures market

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Abstract

Unlike traditional assets, cryptocurrencies lack fundamental information such as dividends, earnings, or cash flows, requiring market participants to rely on alternative sources of information for price discovery and trading decisions. In this study, we analyze the relationship between news sentiment and Bitcoin (BTC) and Ether (ETH) futures returns, as well as net trading positions. We use a dataset of over 9100 BTC and 5400 ETH news articles. The findings reveal that news sentiment is significantly associated with futures price movements and market positioning by professional investors. We extend the traditional dictionary-based approach of Loughran and McDonald (2011) by enabling a more precise identification of crypto-relevant content. Our findings highlight the role of news sentiment as an information channel in cryptocurrency derivatives markets and uncover substantial differences between the BTC and ETH futures markets.

Keywords Cryptocurrency futures · Bitcoin (BTC) · Ether (ETH) · News sentiment analysis · Financial news media

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1 Introduction

In recent years, cryptocurrencies have gained tremendous attention from academics, retail and institutional practitioners, and politicians alike[1]. For example, during the 2024 U.S. presidential campaign, Donald Trump repeatedly expressed his support for cryptocurrencies and the underlying blockchain technology. Following his election victory, the price of Bitcoin increased by approximately 11.5% in a single day. This anecdote illustrates the potential effect of recent news and positive sentiment and highlights the importance of answering the question to what extent the sentiment of news shapes the price mechanism of cryptocurrencies. While a growing body of literature investigates sentiment in cryptocurrency spot markets (see e.g., Liu & Tsyvinski 2021, Aysan et al. 2024, Anamika & Subramaniam 2023, Akyildirim et al. 2024), these studies neglect the pricing dynamics in the more institutionally relevant futures markets.

Since the introduction of the first cryptocurrency-based futures contract in December 2017, professional market participants have gained access to the broader cryptocurrency market and played an essential role in its maturation (Baur & Smales, 2022). Despite the importance of futures markets, there has been no systematic investigation of how the cryptocurrency futures market evaluates sentiment extracted from cryptocurrency-related news. Our study fills this gap by investigating how Bitcoin (BTC) and Ether (ETH) futures prices respond to shifts in sentiment and how institutional investors adjust their market positions.

Existing studies based on sentiment analysis in the context of cryptocurrencies exhibit several limitations, which our paper addresses through multiple key contributions. First, we focus on futures markets rather than spot markets, which are utilized by earlier studies on sentiment and investor attention (see e.g., Anamika & Subramaniam 2022, Aysan et al. 2024, Karalevicius et al. 2018). With the fundamental concept of a decentralized ecosystem without centralized regulation, the spot prices of cryptocurrencies vary between multiple decentralized exchanges, reflecting inconsistent assumptions and thus arbitrage opportunities (Makarov & Schoar, 2020). Spot markets impose constraints on betting against prices, such as limited lendable supply, borrowing costs, short-sale frictions, (Augustin et al., 2023). In contrast, cryptocurrency futures markets offer uniform pricing, high liquidity, and the ability to hedge spot price risks (see e.g. Matic et al. 2023, Sebastião & Godinho 2020).

Given the natural predominance of negative sentiment within news articles, reacting to sentiment changes requires frictionless shorting. As futures allow cost-effective short positions, this makes cryptocurrency futures markets an interesting setting for sentiment analysis that must capture both positive and negative signals. Moreover, trading activity is concentrated in derivatives, with aggregate cryptocurrency futures volumes consistently exceeding spot volumes (Aleti & Mizrach, 2021). At institutional scales, the total transaction cost of futures often undercuts spot because exchange and clearing fees are largely fixed on a per-contract basis and fee tiers decline with volume, which further strengthens the case for futures markets. Finally,

[1] Cryptocurrencies built on the blockchain represent decentralized assets where transactions can be verified even in the absence of a centralized custodian (Makarov & Schoar, 2020).

our analysis relies on an efficient transition of information and sentiment into prices. Initially, shortly after the introduction of Bitcoin futures in December 2017 price discovery occurred in the spot market (Corbet et al., 2018). However, the futures market has matured (Chen & Yang, 2024). Consistent with evidence for equity indices and commodities (Tse, 1999; Figuerola-Ferretti & Gonzalo, 2010), more recent studies (see e.g. Robertson & Zhang 2025, Aleti & Mizrach 2021, Wu et al. 2021, Kapar & Olmo 2019) provide empirical evidence that the futures market now dominates price discovery in cryptocurrencies. Because changes in sentiment are priced first in markets where price discovery occurs, our focus on futures market sharpens the sentiment-return relation and limits microstructure noise from lagging venues.

Second, we explore how professional investors in futures markets react to changes in news sentiment. Earlier studies focus on cryptocurrency spot markets, which show signs of a varying degree of market efficiency (Urquhart, 2016; Chu et al., 2019) and are largely driven by short-term investors, noise traders, and speculators (Aysan et al., 2024). Investment decisions of (unexperienced) retail traders are influenced by phenomena such as herding behavior (Celeste et al., 2020; Gama et al., 2019; Ballis & Drakos, 2020), momentum effects (Liu & Tsyvinski, 2021), or overreaction to events and irrational sentiment on social media (Karalevicius et al., 2018; Kraaijeveld & De Smedt, 2020; Shen et al., 2019). Unlike spot markets driven by retail traders, futures markets attract more sophisticated participants. Following Aysan et al. (2024), we argue that due to the experience and skill of professional investors, irrational sentiment-induced volatility should be less important in futures markets. Consistent with our focus on institutional investors, our sentiment measure is derived from reputable sources such as WSJ, FT, Reuters News, or Coindesk. These sources provide more substantive coverage and rational reporting about relevant developments, such as Bitcoin halving or regulatory standards, thus mitigating the risk of distortion from exaggerated or bot-generated content common in social media.

Third, our study highlights the role of news sentiment, defined as text sentiment of relevant articles in reputable sources, as a key information channel in the pricing of cryptocurrency futures. Unlike retail investors, who often lack the knowledge and resources for a detailed valuation (Aysan et al., 2024), institutional investors rely on sophisticated valuation models to support their trading decisions. However, applying such models to cryptocurrencies is inherently challenging due to the absence of fundamental properties such as dividends, cash flows, or earnings (Aysan et al., 2024). Moreover, there is no uniform opinion on whether the intrinsic value of cryptocurrencies is different from zero (see e.g., Cheah & Fry 2015, Treiblmaier 2022, Van Vliet 2018). In light of this challenge, Treiblmaier (2022) suggests refraining from the term intrinsic value and turning towards the ‘extrinsic value’, which shifts the focus to observable factors that reflect a cryptocurrency’s utility and ecosystem characteristics. Relevant factors include network size and scarcity (Van Vliet, 2018), security (Pagnotta, 2021), utility (García-Monleón et al., 2021), and production costs related to mining expenses (Treiblmaier, 2022)[2]. Reputable news sources provide essential

[2] Note that the broad concept of utility might also intersect with the other properties and that the property of scarcity only applies to BTC.

information about these properties, and news sentiment allows an evaluation of this information accordingly.

Fourth, our paper contributes methodologically by improving sentiment measurement in the context of crypto-related news[3]. In contrast to existing studies such as Anamika and Subramaniam (2023) and Aysan et al. (2024), which rely on ex-post sentiment measures from external data providers, our approach constructs sentiment scores internally using publicly available news data and can be applied in real time. Validity concerns can be reduced by avoiding reliance on proprietary and often opaque scores from external data providers that could be reverse-engineered to fit financial outcomes. Furthermore, while Anamika and Subramaniam (2022) rely on news headlines, we measure sentiment based on the entire body of the article, allowing for a deeper and holistic analysis. Finally, we augment the Loughran and McDonald (2011) dictionary-based sentiment measure with GenAI, addressing the concern that a dictionary approach captures only one dimension of sentiment and neglects the frequency of the appearance of certain context-specific expressions (see e.g., Calomiris & Mamaysky 2019). We use GenAI to derive a crypto-specific dictionary from a wide range of context-specific glossaries, technical sources, such as Nakamoto (2008), and crypto-related academic publications. The resulting dictionary comprises nearly 150 distinct terms[4], which we use to construct a crypto density weight (CDW). This measure enables us to down-weight sentiment derived from non-crypto-related information, thereby providing a more targeted assessment of crypto-specific sentiment.

Our final dataset consists of more than 9100 BTC-related and 5400 ETH-related news items, which are aggregated daily. We find a significant relation between news sentiment and futures returns if we account for the *CDW* within the sentiment approach, but not in the case of using the Loughran and McDonald (2011) dictionary-based sentiment. Splitting sentiment into positive and negative values provides additional insights. For BTC, negative news sentiment is associated with lower futures returns, whereas for ETH, positive news sentiment is associated with higher futures returns.

In addition, our analysis reveals that futures net trading positions are related to sentiment. Hedgers (speculators) increase their long (short) positions during periods of strong positive sentiment, suggesting active portfolio adjustments by professional investors. Interestingly, also ETH futures returns and net trading positions are driven by BTC news rather than ETH news sentiment. Our results hold for different market phases.

This paper proceeds as follows. Section 2 derives our theoretical reasoning. In sect. 3, we describe our data and report descriptive statistics. Sections 4 present empirical results for BTC and ETH futures, while sect. 5 implements further robustness tests. Finally, sect. 6 concludes the study.

[3] Of course, it is not news texts and their sentiment, but always market actors that drive prices. However, sentiment analysis enables us to extract positive or negative values that certain news may have for the market.

[4] A list of these words, along with a figure illustrating the frequency of the 15 most common dictionary terms in BTC articles, is provided in the Appendix Table 7.

2 Theoretical development

2.1 Literature review

Value drivers of cryptocurrencies

At the outset of any analysis of value-driving news, the question of what determines the value of cryptocurrencies needs to be addressed. As stated by Treiblmaier (2022), the notion of intrinsic value is not particularly useful for the analysis of the value of cryptocurrencies. Some even stick to the opinion that the intrinsic value of cryptocurrencies essentially is zero (Cheah & Fry, 2015). Therefore, as suggested by Treiblmaier (2022), we rather focus on the concept of 'extrinsic value' of cryptocurrencies, which appears to be more easily determinable.

We consider five attributes, that can be used by market participants to determine the value of a cryptocurrency. These attributes are: network value and scarcity (see Van Vliet 2018 for both), security (Pagnotta, 2021), utility (García-Monleón et al., 2021) and cost of production (Treiblmaier, 2022). Note that these five aspects are not necessarily independent of each other, as for instance security issues may negatively influence the utility. Additionally, the supply-side cost of production argumentation, which only can deliver a minimum value, is entirely different to the other four dimensions, which are demand-side oriented.

The objective of this study lies in news texts. Thus we consider aspects that may be present in news and that have the potential to exert a qualitative influence on the value of cryptocurrencies. For instance, the emergence of a novel regulatory framework that enhances safety standards could be a positive influence. To this end, we discuss to what extent the five mentioned attributes may play different roles in the value determination of BTC and ETH.

Scarcity: Clearly, part of the value of Bitcoin is based on the fixed supply cap of 21 million full coins (implemented through predictable halving cycles) (Pagnotta & Buraschi, 2018). In contrast, Ether is not generally built on the concept of scarcity, but post-EIP-1559[5], its so-called burn mechanism implies some scarcity effects. In summary, the impact of scarcity is more pronounced in BTC than in ETH.

Network value: According to Metcalfe's Law the value of a network is proportional to squared number of its users (Van Vliet, 2018). Thus, the value of BTC may be high simply because of the fact that it is the absolutely leading cryptocurrency (Zhang, 2023). However, also ETH has some advantageous properties, as Ethereum token holders benefit from both Ethereum's growth and the growth of any application built on the platform (Celeste et al., 2020). Summarizing, we can state that the network value is a core component for both Bitcoin and Ether.

[5] The term post-EIP-1559 refers to the period subsequent to August 5, 2021, which marked the implementation of Ethereum Improvement Proposal (EIP) 1559. This implementation introduced significant economic improvements to the Ethereum network (Li et al., 2025).

Security: According to Pagnotta and Buraschi (2018), Bitcoin with its proof-of-work (PoW) mechanism requires the control of 51% of the total mining hash power to manipulate transactions. As such a control would be extremely expensive, the BTC network is considered very reliable. Ethereum's proof-of-stake (PoS) security model is based on economic finality, validator honesty enforcement (through slashing), and financial risk-return mechanics, differentiating it from PoW designs, but making it also very secure (Chen & Vinogradov, 2021). One can summarize that both the ETH and the BTC network appear to be highly secure (as of now), but use different mechanisms.

Utility: The utility of Bitcoin as a medium of exchange is weak and the value storage use case is not classical utility (Zhang, 2023). Thus the valuation-impact of utility appears to be rather low for Bitcoin (Pagnotta & Buraschi, 2018). Compared to Bitcoin, which is a standalone application operating on its foundational blockchain, Ethereum enables the execution of smart contracts on its blockchain, and thereby facilitates the development of decentralized applications. Ethereum token holders benefit not only from the expansion of the Ethereum network but also from the success of any application developed on the platform, which may be seen as an advantage to Bitcoin (Celeste et al., 2020). The valuation of Ether is fundamentally connected with the utility that is derived from these smart contracts and corresponding applications (such as dApps, DeFi, staking, NFTs) (Cong et al., 2020).

Cost of production: Because of Bitcoin's energy intensive mining process (Pagnotta & Buraschi, 2018) due to the PoW consensus mechanism, which requires significant computational power and energy and which is not anymore in work for ETH (Abraham & El-Chaarani, 2022), it is relatively obvious that in Bitcoin the cost-of-production (energy, hardware etc.) aspect is much stronger than in ETH.

Given the distinct characteristics of BTC and ETH, it is reasonable to anticipate possibly divergent reactions of the respective prices to specific news events. Conversely, certain developments may impact both cryptocurrencies in a comparable manner.

Futures on cryptocurrencies

The importance of BTC and ETH futures markets has grown enormously since their introduction in 2017 for BTC (Alexander & Heck, 2020) and in 2021 for ETH (Kristjanpoller et al., 2024). According to Baur and Smales (2022), cryptocurrency futures add two features, namely allowing institutional investors to trade a regulated cryptocurrency product and improving market efficiency by enabling shorting of BTC and ETH.

While cryptocurrencies are a very special underlying asset that is traded on many exchanges around the world simultaneously, the general relationship between the spot market price and the futures price via the cost-of-carry model is still valid in these markets. Shi et al. (2024) show that while futures-price deviations (basis risk) often appear, especially during volatility spikes, arbitrage trading corrects these inefficiencies. Kristjanpoller et al. (2024) studies the spot and futures market interaction for ETH, for which the arbitrage also appears to function.

Earlier works on the price discovery of BTC futures vs. spot markets such as Entrop et al. (2020) documents unclear or varying relationships. However, after some years, it appears indisputable that the BTC futures market generally has a lead over the spot markets, in the sense that price discovery takes place in the futures markets (Frino et al., 2025; Chen & Yang, 2024; Akyildirim et al., 2020). Regarding ETH, there appears to be no study that clearly proves the price discovery with regard to CME futures[6], however, Augustin et al. (2023) reveal that the introduction of the ETH future on the CME improved the price-synchronicity of ETH–USD pairs, which indicates that this future also contributes to a better pricing. In addition to research focusing on futures markets and price discovery, related work has examined risk management in cryptocurrency derivatives. Matic et al. (2023) emphasize that effective risk management in more volatile market regimes requires richer models and multi-dimensional hedging. This complements the literature on cryptocurrency futures by highlighting the broader role of derivatives not only in price discovery but also in mitigating extreme risks.

Altogether there are clear indications that cryptocurrency futures markets are mature markets that are functionally related with the spot markets and they are the playing field of the professionals.

Sentiment analysis

Sentiment in financial markets, especially stock markets, has long been a subject of research. The foundational work of Baker and Wurgler (2006), upon which numerous subsequent studies have been built, provides an overview of several proxies for investor sentiment, including: investor surveys, retail investor trades, mutual fund flows, trading volume, dividend premium, IPO returns, option implied volatility, IPO volume or insider trading. Baker and Wurgler (2006) also develop an index that aggregates several of these dimensions.

An additional dimension to sentiment analysis is added by inferring sentiment from text such as social media posts (Kim & Kim, 2014) or news (Smales, 2014). These approaches aim to quantify the sentiment of market participants and analyze their potential influence on market developments. There is evidence that sentiment tends to correlate negatively with returns in the long term (Baker & Wurgler, 2006; Schmeling, 2009) and positively with contemporaneous returns (Brown & Cliff, 2004). However, the predictive power of sentiment is inconclusive and turns out to be rather weak in many empirical studies (e.g., Brown & Cliff 2004).

Texts are a particularly interesting source of sentiment. Social media texts tend to represent irrational sentiment (Li et al., 2023), but news texts in reputable media outlets also express sentiment. Rather than reflecting investor mood, they reflect whether the news is good or bad (Schumaker et al., 2012).

[6] Interestingly, the ether perpetual swap on BitMEX, an unregulated cryptocurrency derivative exchange, showed price discovery over the major spot exchanges in the years before the establishment of the CME future (Alexander et al., 2020).

Sentiment in crypto markets has been addressed in various publications. One strand of literature examines irrational or emotional sentiment proxied by tweets on X (Twitter). (Kraaijeveld & De Smedt, 2020), for example, show that the sentiment extracted from Twitter messages can predict cryptocurrency spot returns. Shen et al. (2019) provides evidence that investor attention, proxied by the number of Twitter tweets referring to Bitcoin, predicts spot volatility and trading volume.

Another strand of literature uses Google search trends as a proxy for the degree of investor pessimism or fear in response to economic or geopolitical crises. Prior research shows that household- and investor-level crisis sentiment indicators derived from Google Trends are associated with cryptocurrency price movements (see e.g., Liu & Tsyvinski, 2021; Burggraf et al., 2021), crash risk (see e.g., Anastasiou et al. 2021), and price clustering (Baig et al., 2019).

Using Thomson Reuters MarketPsych, Akyildirim et al. (2025) show that DeFi coin-specific sentiment indices are linked to DeFi coin returns. Rognone et al. (2020) show that BTC/USD spot prices incorporate news sentiment differently than major FX pairs. Anamika and Subramaniam (2023) find that Bitcoin shows positive returns when investors are optimistic about Bitcoin. At the same time, an overall optimistic sentiment in the equity market (proxied by the Baker and Wurgler (2006) sentiment index or the VIX index) is negatively related to Bitcoin spot returns. Sapkota (2022) demonstrates a long-term relation between the sentiment of financial news and Bitcoin's volatility. Karalevicius et al. (2018) use a lexicon-based approach to derive sentiment from various Bitcoin-related sources, such as CoinDesk. They document a significant positive relation between sentiment and Bitcoin spot prices and argue that investors tend to overreact in the short run. Anamika and Subramaniam (2022) show that investors' sentiment, extracted from news headlines, affects cryptocurrency spot returns. When news sentiment is positive and investors are bullish about Bitcoin, spot prices increase. Aysan et al. (2024) analyze the relationship between price spikes and news sentiment in diverse cryptocurrencies by using Thomson Reuters MarketPsych Analytics. The findings of this study indicate that specific news themes are associated with significant increases in the price of cryptocurrencies. Akyildirim et al. (2024) document that sentiment is linked to spillover in cryptocurrency spot prices, with social-media-based sentiment measures exhibiting a stronger relationship than traditional news.

2.2 Hypothesis development

Consistent with Treiblmaier (2022), we frame cryptocurrency valuation in terms of extrinsic value rather than intrinsic value. This concept centers around observable attributes or characteristics, such as network value and scarcity, security, utility, and cost of production. Importantly, these determinants of extrinsic value are shaped by continuous advancements in technology, shifts in regulatory frameworks, and evolving socio-political dynamics, which are arguably initially communicated to market participants via the traditional and social news media.

While both news media and social media distribute information relevant to cryptocurrency markets, the latter presents substantial challenges for sentiment analysis, questioning the reliability of these analyses. Social media language is often informal and relies on sarcasm, exaggeration, misplaced or excessive punctuation, and whole content might be bot-generated (Balahur, 2013). In contrast, articles from reputable news sources follow journalistic and linguistic standards and offer more rational, balanced, and economically relevant reporting (see e.g., Vasterman 2005). We focus on news sentiment, which we conceptualize as a more rational type of information signal. News sentiment offers a transparent and tractable way of interpreting the information. It enables the quantification of the directional tone of value-relevant developments and signals and allows us to links them to futures price movements.

In efficient markets, institutional investors are expected to process this information and adjust their positions or trading decisions accordingly, translating these information signals into prices. For example, favorable regulatory announcements or technological advancements should strengthen the perceived value of a cryptocurrency, whereas negative developments, such as security breaches or obstructive regulation, should have the opposite effect. Therefore, we hypothesize that positive (negative) news sentiment will be associated with increases (decreases) in cryptocurrency futures prices. Due to structural and functional differences between BTC and ETH, we expect that BTC prices can react differently to certain news than ETH prices. At the same time, some developments can similarly affect both cryptocurrencies[7].

Hypothesis 1a: *BTC futures returns are positively related to the news sentiment.*

Hypothesis 1b: *ETH futures returns are positively related to the news sentiment.*

Previous studies on commodity markets document that commodity returns often react asymmetrically to news sentiment, with negative sentiment evoking stronger market responses than positive sentiment (Maghyereh et al., 2020; Smales, 2014). This asymmetry may arise from psychological biases such as the influence of sentiment on the risk tolerance of investors and thus the investment decisions in speculative assets (see e.g., Kuhnen & Knutson 2011; Maghyereh et al. 2020). For example, in a market where overall sentiment is bullish, positive news may be largely anticipated, whereas negative news may challenge prevailing expectations and trigger sharper reactions. Dorfleitner and Zhang (2024), who focus on ESG news sentiment, similarly document asymmetric market responses. Given the differences in the BTC and ETH ecosystems, we also expect potential differences in how each futures contract reacts to positive or negative news sentiment[8].

Hypothesis 2a: *The relation between BTC futures returns and news sentiment differs for negative and positive news with respect to magnitude.*

[7] Note that if there were only irrational market participants who did not trade based on value-reflecting information, there would be no correlation with news sentiment. While we do not expect such an effect, this would still be a possible outcome of an empirical investigation.

[8] Again, it is conceivable that the reaction is symmetric if there is no positive or negative default setting for cryptocurrencies.

Hypothesis 2b: *The relation between ETH futures returns and news sentiment differs for negative and positive news with respect to magnitude.*

In the absence of fundamental determinants, institutional traders in cryptocurrency futures markets arguably rely on sentiment-driven signals to guide their investment decisions. The Commitment of Traders (COT) reports from the US Commodity Futures Trading Commission (CFTC) categorize these traders into hedgers (commercials) and speculators (non-commercials). Several academic studies highlight the role of these groups of traders.

Lehecka (2015) finds that hedging and speculative position behavior display no explanatory power for the development of a broad range of commodity futures prices. Instead, a reaction of net positions to price development can be observed (Lehecka, 2015). Regarding oil futures market, Bu (2011) finds that net positions significantly positively influence oil futures returns. If speculators take more long positions, it has a positive effect on oil futures returns. In contrast, returns fall when speculators take increasingly short positions (Bu, 2011). Even in the field of the gold futures market, Smales (2014) find the impact of net trader positions on the sentiment-return relationship.

In the context of cryptocurrencies, we argue that in the absence of fundamental data, even institutional investors and professional traders can utilize the news sentiment along with the recent price movements. Thus, we also expect a relationship between the net positions of speculators and hedgers in the BTC and ETH futures market and news sentiment. If the news sentiment and the returns have been positive for a while, then the natural thing for speculators will be to trade the reversal, i.e. go short, and vice versa for hedgers[9]. However, the effect depends on the time frame to be investigated. In the very short run, positive sentiment can lead to self-reinforcing momentum trades from speculators (Caporale & Plastun, 2020), whereas over a longer time horizon, price reversals can be expected (Karalevicius et al., 2018). Therefore, we hypothesize that the net trading positions (long minus short) of speculators and hedgers reflect the interpretation of sentiment signals for these two groups of traders.

Hypothesis 3a: *The net trading positions of speculators and hedgers in the BTC futures market are related to news sentiment.*

Hypothesis 3b: *The net trading positions of speculators and hedgers in the ETH futures market are related to news sentiment.*

[9] In a situation where the hedgers' position is predominantly long, it's natural that speculators are predominantly short and vice versa. This follows from both groups providing liquidity to each other.

3 Data & methodology

3.1 Baseline news sentiment

Sentiment analysis and classification are subfields of Natural Language Processing (NLP), which entails extracting meaningful information from textual data and categorizing it as positive, neutral, or negative (Saju et al., 2020). The most common approach relies on predefined dictionaries that label words as positive or negative[10]. This method assesses sentiment by calculating the proportion of positive and negative words relative to the text length (see e.g., Loughran & McDonald 2011, Shapiro et al. 2022). A text with more positive than negative words is classified as positive, and vice versa.

Naturally, the classification of words as positive, negative, or neutral depends on the context. For example, the words “Whale", “HODL", or “rug pull" have little to no specific connotation in traditional economics but are crucial in the cryptocurrency space. Since this study focuses on financial news, we utilize the Loughran and McDonald (2011) dictionary as a baseline sentiment measure (*Sent*)[11], which categorizes words based on their financial meaning and is calculated as follows:

$$Sent = \frac{\#positive\ words - \#negative\ words}{\#all\ words} \tag{1}$$

with *Sent* ranging from −1 (very negative) to +1 (very positive) (Saju et al., 2020). The analysis is based on Bitcoin- and Ethereum-related news articles obtained from the Eikon News Monitor, provided by LSEG[12], which, due to their accessibility and broad coverage, represent news sources of particular interest to professional futures investors. All news items are extracted from the Bitcoin and Ethereum workspace. Our dataset comprises both the headlines and full texts of news articles from a range of crypto- and finance-focused sources (e.g., CoinDesk, Financial Times, Wall Street Journal, Refinitiv, Business Standard), covering the period from October 25, 2022, to August 30, 2024. To ensure high data quality, we implement standard preprocessing and cleaning procedures. Specifically, we convert all text to lowercase, apply lemmatization, and exclude live market updates or feeds that merely report past market movements.

For a structured daily time series, individual sentiment scores are aggregated by calculating the daily mean. Our dataset includes over 9,100 BTC and over 5,400 ETH

[10] Dictionary-based sentiment analysis is widely used in accounting (e.g., Bochkay et al. 2023, Henry & Leone2016), financial research (e.g., Loughran & McDonald 2020; Kearney & Liu 2014; Heston & Sinha 2017; Gotthelf & Uhl 2019; Smales 2014), macroeconomic forecasting (e.g., Barbaglia et al. 2023, Ashwin et al. 2021, Lunde & Torkar 2020), and private consumption analysis (e.g., Uhl 2011).

[11] Note that this procedure may also fall under the term *news tone*. However, in accordance with the academic literature, this study employs the term news sentiment. While news sentiment generally refers to the broader, quantifiable orientation of news content (positive, negative, neutral), news tone emphasizes the stylistic nuance in how information is conveyed (e.g., optimistic vs. pessimistic). Thus, news tone can be understood as a more specific manifestation within the broader concept of news sentiment. In this work, the rational component of our sentiment measure may alternatively be interpreted as rational news tone.

[12] London Stock Exchange Group, formerly Refinitiv.

news items. The overlap between BTC and ETH news amounts to approximately 1700 news items, representing about 33% of ETH news and 19% of BTC news.

Aggregation at the daily level results in a total of around 460 news items, of which approx. 90% are classified as negative and 10% as positive. The significant predominance of negative news leads to an unbalanced sample, which should be taken into account when interpreting the results and statistical metrics.

3.2 Cryptocurrency glossary and dependency—a novel news sentiment approach

While the Loughran and McDonald (2011) dictionary is widely used for financial news, it does not account for crypto-specific terms or expressions. Calomiris and Mamaysky (2019) claim that an article's sentiment reflects only one aspect while the frequency of specific words or phrases might also be relevant.

Inspired by Engle et al. (2020), we address the significant role of context-dependent language in interpreting topic-specific news sentiment and develop a cryptocurrency-specific dictionary. To derive an extensive list of relevant terms, we utilize GenAI, particularly ChatGPT. To ensure broad coverage, we provide ChatGPT with a diverse range of crypto-focused texts, including the Bitcoin whitepaper (Nakamoto, 2008), glossaries from crypto-centric websites, and academic publications. This resulted in a crypto-specific dictionary comprising around 150 context-relevant terms like, for example, Bitcoin, Blockchain, Altcoin, Whale, and Rug Pull.

Our approach addresses challenges in evaluating the sentiment of crypto-related news articles. Crypto-specific terms such as “blockchain" or “bitcoin" inherently lack a positive or negative meaning. Thus, those words do not influence news sentiment measures but serve as buzzwords for investors when interpreting news. Therefore, many news articles contain information that extends beyond purely crypto-specific content. To address this issue, we measure the crypto-relevant content of a news item and weight the sentiment accordingly. By incorporating both the crypto density weight (CDW) and the sentiment score (Sent) from the dictionary-based approach, we calculate the overall crypto-specific sentiment ($Sent^{Crypto}$) as a weighted sum.

Let N be the number of news items on a particular day, n_i^{crypto} represents the number of crypto-specific words (derived from our GenAI-cerated crypto-dictionary) in article $i \in N$ and n_i^{total} is the total number of sentences within this article. We define

$$CDW_i := \frac{n_i^{crypto}}{n_i^{total}}.$$

Moreover, $Sent_i$ represents the sentiment as in Eq. (1). Finally, we define our overall daily crypto-specific sentiment ($Sent^{Crypto}$) as the average of the density-weighted sum of daily article sentiments

$$Sent^{Crypto} := \frac{1}{N} \sum_{i=1}^{N} \left(CDW_i \cdot Sent_i \right). \tag{2}$$

Descriptive statistics are displayed in Table 1. The correlation between the BTC and ETH crypto-specific sentiment measures is approximately 0.36.

3.3 Futures market

We use cash-settled BTC and ETH futures contracts with an underlying size of five BTC (ETH), which are the most liquid cryptocurrency futures listed on the CME. Futures prices are from the CME Group exchange[13]. The CME Group is the largest provider of derivative financial instruments across all major asset classes, including interest rates, equity indices, currencies, energy, agricultural products, metals, and cryptocurrencies. In the area of Bitcoin futures trading, it is the second-largest exchange globally [41]. Moreover, there has been a significant increase in Bitcoin futures volume over the past years. While CME Bitcoin Futures recorded a monthly

Table 1 Descriptive statistics

Variables	N	Min	Pctl(25)	Median	Pctl(75)	Max	Mean	St. Dev.
Measurement of sentiment								
$Sent_{t,BTC}$	461	−0.0845	−0.0305	−0.0208	−0.0123	0.0212	−0.0214	0.0138
$Sent^{Crypto}_{t,BTC}$	461	−0.0733	−0.0221	−0.0141	−0.0065	0.0239	−0.0147	0.0125
$Sent_{t,ETH}$	459	−0.0608	−0.0195	−0.0111	−0.0029	0.0253	−0.0113	0.0136
$Sent^{Crypto}_{t,ETH}$	459	−0.0951	−0.0175	−0.0099	−0.0028	0.0405	−0.0106	0.0132
Control variables								
$R_{t-1,BTC}$ (in %)	461	−14.6574	−1.5279	−0.0508	1.8415	12.9842	0.1144	3.1179
$R_{t-1,ETH}$ (in %)	459	−20.3066	−1.7399	0.0217	1.7420	14.3512	−0.0019	3.3806
$Irrational_{t,BTC}$	461	−0.0777	−0.0155	−0.0039	0.0113	0.0944	−0.0026	0.0220
$Irrational_{t,ETH}$	459	−0.1537	−0.0195	0.0120	0.0424	0.5515	0.0151	0.0619
$DJIA\ log\ return_t$	461	−2.6365	−0.3764	0.0815	0.4741	3.6285	0.0550	0.7593
$USDI\ log\ return_t$	461	−1.3022	−0.1770	−0.0224	0.1726	0.9690	−0.0103	0.3196
$FFR\ log\ return_t$	461	−0.2186	0.0000	0.0000	0.0000	21.7935	0.1190	1.2579
$CPI\ surprise_t$	461	−0.7804	0.0000	0.0000	0.0000	0.4772	−0.0028	0.0707
$PPI\ surprise_t$	461	−1.5376	0.0000	0.0000	0.0000	1.2208	−0.0024	0.1519
$CapUt\ surprise_t$	461	−1.1465	0.0000	0.0000	0.0000	1.6751	−0.0054	0.1603
$PersIn\ surprise_t$	461	−0.8448	0.0000	0.0000	0.0000	1.3621	0.0028	0.1134
$UER\ surprise_t$	461	−1.3291	0.0000	0.0000	0.0000	0.7580	−0.0005	0.1012
$GDP\ surprise_t$	461	−0.5070	0.0000	0.0000	0.0000	1.3078	0.0047	0.0856
Recession dummy	461	0	0	0	0	1	0.2126	0.4096
Weekly net position of hedgers and speculators								
Speculators$_{BTC}$	95	−0.1138	−0.0617	−0.0290	0.0138	0.1447	−0.0188	0.0569
Hedgers$_{BTC}$	95	−0.1694	−0.0350	−0.0019	0.0237	0.0602	−0.0131	0.0528
Speculators$_{ETH}$	94	−0.2617	−0.1693	−0.0883	0.0009	0.3032	−0.0660	0.1388
Hedgers$_{ETH}$	94	−0.2813	−0.0608	−0.0094	0.0697	0.1706	−0.0055	0.1067

This table presents the lower and upper quartiles, median, mean, standard deviation, minimum, and maximum of our employed variables. Our sample ranges from om 25.10.2022 to 30.08.2024. Note that data on net trading positions for hedgers and speculators are published weekly

[13] The underlying price is defined as the CME CF Bitcoin Reference Rate (BRR), which is a once-a-day benchmark for Bitcoin spot prices that is calculated as a volume-weighted median of trade data from multiple eligible cryptocurrency exchanges.

volume of around 9,500 in December 2017, this figure surged to approximately 80,000 by December 2018. However, the volume continues to grow from about 279,000 in October 2022 to roughly 601,000 in October 2024[14]. The returns of futures prices are calculated using the logarithmic returns.

Net trading positions of speculators and hedgers are derived from the weekly Commitment of Trades (COT) reports for commodity futures by the US Commodity Futures Trading Commission (CFTC). These reports provide data on futures positions (long and short positions) for various trader groups and various commodity futures. Additionally, this information is also available for BTC and ETH futures. Traders are categorized into three groups. If the purpose of the futures positions is hedging, they are assigned to the "commercial" category. If market participants speculate on certain market movements, they are categorized as "non-commercial". Futures traders who do not meet a certain size threshold are categorized in a third category, "Non-reportable".

Each category has a detailed breakdown of long and short positions on weekly basis. In line with related research on futures markets (see e.g. Smales 2014), we ensure comparability and standardize the weekly net positions (long-short) for both categories on the basis of the corresponding weekly open interest. For example, a negative value of the net position of non-commercial traders (Speculators) may indicate a bearish sentiment among speculative market participants. In contrast, a positive value of commercial traders (Hedgers) net trading position may suggest a bullish outlook from Hedgers. The higher the value, the greater the divergence in market expectations between commercial and non-commercial traders.

3.4 Control variables

In our empirical setting, we control for several macroeconomic as well as crypto-specific indicators. The descriptive statistics for all variables are shown in Table 1.

Christie-David et al. (2000) and Cai et al. (2001) observed an effect of the release of the following macroeconomic indicators on gold futures returns: Consumer Price Index (CPI), Producer Price Index (PPI), Capacity Utilization (CapUt), Personal Income (PersIn), Unemployment Rate (UER), and Gross Domestic Product (GDP)[15]. The data for this analysis stem from the "Economic Events Monitor" of Refinitiv Eikon. Economic growth values are published quarterly, while the rest of the indicators are released monthly. In line with Smales (2014), these variables are additionally standardized to account for the different units of the indicators (Balduzzi et al., 2001).

To aggregate the monthly or quarterly datasets to a daily basis, days on which no data was published are set to zero. The zero represents the situation of already priced-in expectations (no surprise). Non-zero values exhibit differences between expectations and reality. By utilizing these surprise variables, we account for unexpected macroeconomic events.

In addition to the macroeconomic indicators, we also add several crypto-specific control variables. In this field, Bouri et al. (2020) point to the effect of monetary pol-

[14] For more information, see monthly CME Exchange volume reports on https://www.cmegroup.com/.

[15] All indicators refer to the U.S. economy, to display the view of US investors.

icy on Bitcoin returns and volatility. Zhu et al. (2017) observe the Dow Jones Industrial Average (DJIA), the U.S. Dollar Index (USDI), and the Fed Funds Rate (FFR) as influencing factors on the Bitcoin price. Therefore, these indicators, obtained from the Federal Reserve Bank of St. Louis, are also considered in the analysis.

To control for irrational sentiment for cryptocurrency c, $c \in \{BTC, ETH\}$, we use the $Irrational_c$ variable, which is extracted from MarketPsych (MP) news and social media sentiment. The MP social media sentiment value reflects euphoria, whereas the MP news sentiment reflects all the rational news sentiment. Both items are also highly correlated, since many news may also be widely discussed on social media. This results in a high correlation of 0.8. To extract the irrational sentiment part of MP social media news sentiment, the $Irrational_c$indicator is calculated as the difference between social media sentiment and news sentiment, with the latter being weighted by using the $\text{Social media} = \beta \cdot \text{News}$ regression coefficient.

4 Relationship between futures returns and news sentiment

4.1 Overall news sentiment

To explore the relationship between news sentiment and cryptocurrency futures returns (Hypothesis 1a/1b), we begin by examining the link between daily BTC/ETH futures returns and aggregated crypto-weighted measures of news sentiment ($Sent^{Crypto}$). Drawing upon the argumentation of Smales (2014), we implicitly assume that news articles are hardly influenced by (BTC or ETH) futures returns. Nevertheless, to further overcome the potential issue of endogeneity—in the sense that positive (negative) returns might be reflected as positive (negative) sentiment in contemporary news reports—we exclude pure market updates and buzz feeds, which primarily report past (crypto) market movements from our primary data set. However, with an average of approximately 30 news items per day, the overall impact of such scarce reports is limited.

We apply a regression model of the form

$$\begin{aligned} R_{t,c} = \beta_0 + \sum_{j=0}^{3} \beta_{j+1} News_{t-j,c} + \sum_{y=1}^{4} \theta_y Crypto-macro_{y,t} \\ + \sum_{\tilde{y}=1}^{6} \gamma_{\tilde{y}} Macro_{\tilde{y},t} + \delta_k X_{k,t} + \epsilon_t \end{aligned} \tag{3}$$

In this model, $R_{t,c}$, $c \in \{BTC, ETH\}$, represents the daily log return of the BTC/ETH futures price (in %). The news sentiment during period t, incorporating both contemporaneous and lagged observations (i.e., $t-1, t-2, t-3$), is represented by the sentiment vector $News_{t,c}$ for each cryptocurrency c. Formally, $News_{t,c}$ denotes the sentiment measure associated with cryptocurrency c, which may correspond either to the baseline sentiment ($Sent_{t,c}$) or to the crypto-specific sentiment ($Sent_{t,c}^{Crypto}$).

The set of macroeconomic factors $Macro_{y,t}$ mirrors new macroeconomic information, including the Consumer Price Index, Producer Price Index, Capacity Utilisation, Personal Income, Unemployment Rate, and Gross Domestic Product. In particular, we control for the difference between expected and actual (economic) effects ("surprise effect") and therefore follow the procedure of Smales (2014).

Additionally, we include crypto-specific macroeconomic controls, represented by $Crypto - macro_{y,t}$, including the returns of the Dow Jones Industrial Average, the US Dollar Index, and the Fed Funds Rate (Zhu et al., 2017). Furthermore, this matrix entails the irrational sentiment variable $Irrational_{t,c}$. $X_{k,t}$ includes the previous day's BTC/ETH futures return and a possible day-of-the-week effect as two control variables, analogous to Smales (2014). ϵ_t represents the error term. To correct for potential serial correlation issues, we implement Newey-West standard errors with Akaike-information-criterion (AIC) to identify the appropriate lag length.

4.1.1 BTC futures returns and BTC news sentiment relation

Columns (1)–(4) of Table 2 present the results for BTC futures. We identify a positive and strongly significant relationship between the crypto-specific sentiment measure ($Sent_{t,BTC}^{Crypto}$) and the logarithmic returns of BTC futures ($R_{t,BTC}$), suggesting that returns increase as BTC news sentiment becomes more positive. Even after accounting for all control variables, a one-standard-deviation increase in sentiment (0.0125) is associated with an economically significant 0.46% increase in $R_{t,BTC}$. Conversely, returns decline as sentiment deteriorates, supporting Hypothesis 1a. When examining the baseline sentiment measure proposed by Loughran and McDonald (2011) ($Sent_{t,BTC}$), the equal weighting of all news content appears to attenuate this relationship. In particular, the coefficients exhibit only a weakly significant contemporaneous positive association (at the 10% level) in column (4). This finding underscores the importance of tailoring sentiment measures to crypto-specific value drivers.

The significantly negative coefficients of the lagged sentiment variable (at $t-3$) across both sentiment measures suggest a potential overreaction to news, which is subsequently corrected in the following days. Notably, in the case of the weighted sentiment measure, the magnitude of the reversal effect is smaller than that of the contemporaneous impact. Column (2) also reveals an earlier indication of this reversal through a significant negative coefficient on $Sent_{t-2,BTC}^{Crypto}$. Furthermore, the correction to the initial reaction does not appear to occur immediately. Instead, investor behavior suggests a "wait-and-see" approach, introducing a temporal delay before sentiment reversals materialize in market prices.

Four out of the six macroeconomic surprise variables are found to be statistically insignificant, indicating no discernible relationship with BTC futures returns. In contrast, the variable $CapUt\ surprise_t$ exhibits a positive and highly significant relationship at the 1% level. This may be attributed to its role as an indicator of surprises in overall economic performance, reflecting the current level of economic output relative to its potential maximum output. Higher capacity utilization signals a stronger economic environment, which tends to support the performance of riskier asset classes, such as equities (Nelson, 1989). In this context, Al-Khazali et al. (2018) high-

Table 2 The Relationship between news sentiment and cryptocurrency futures returns

	Dependent variable: $R_{t,c}$ with $c = BTC$				Dependent variable: $R_{t,c}$ with $c = ETH$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Sent^{Crypto}_{t,c}$	27.8249**	30.0176***			16.8175	
	t = 2.2895	t = 2.5996			t = 1.5581	
$Sent^{Crypto}_{t-1,c}$	6.4088	8.9035			−8.5399	
	t = 0.4810	t = 0.7163			t = −0.7571	
$Sent^{Crypto}_{t-2,c}$	−19.5072	−23.3770**			8.6649	
	t = −1.6270	t = −2.2578			t = 0.6878	
$Sent^{Crypto}_{t-3,c}$	−25.5870*	−27.6134*			−10.7358	
	t = −1.6734	t = −1.8842			t = −0.8077	
$Sent_{t,c}$			13.2524	16.7487*		14.7174
			t = 1.2209	t = 1.7362		t = 1.3764
$Sent_{t-1,c}$			4.3029	5.0424		2.7950
			t = 0.3800	t = 0.4618		t = 0.2782
$Sent_{t-2,c}$			−4.2034	−12.7909		10.9881
			t = −0.3649	t = −1.2535		t = 0.9057
$Sent_{t-3,c}$			−29.4792*	−27.9842**		−9.2383
			t = −1.9368	t = −2.0955		t = −0.7601
$R_{t-1,c}$	−0.0575	−0.0618	−0.0460	−0.0476	−0.0024	−0.0063
	t = −0.8309	t = −0.9378	t = −0.6645	t = −0.7186	t = −0.0451	t = −0.1102
$Irrational_{t,c}$		13.3022*		13.5542*	−0.6056	−0.2868
		t = 1.8296		t = 1.8567	t = −0.2556	t = −0.1241
DJIA log return$_t$		1.2175***		1.2255***	1.3367***	1.3139***
		t = 5.2891		t = 5.3205	t = 5.3316	t = 5.2233
USDI log return$_t$		−0.9576**		−0.9641**	−1.3974***	−1.4289***
		t = −2.2384		t = −2.2815	t = −2.6694	t = −2.7424
FFR log return$_t$		0.0247		0.0409	0.0783	0.0819
		t = 0.3469		t = 0.6178	t = 1.0966	t = 1.1771
CPI surprise$_t$		0.5666		0.5298	0.2583	0.3142
		t = 0.2012		t = 0.1929	t = 0.0736	t = 0.0888
PPI surprise$_t$		−1.0068		−0.9928	−0.8406	−0.8799
		t = −1.1870		t = −1.1142	t = −1.0882	t = −1.1104
CapUt surprise$_t$		3.5280***		3.4065***	3.4554***	3.5237***
		t = 4.9119		t = 4.8607	t = 5.3040	t = 5.4936
PersIn surprise$_t$		0.0628		−0.0633	0.0254	−0.1342
		t = 0.0671		t = −0.0663	t = 0.0254	t = −0.1292
UER surprise$_t$		0.8196		0.7789	−0.1297	−0.2837
		t = 1.0762		t = 1.0232	t = −0.1136	t = −0.2588
GDP surprise$_t$		1.4283**		1.1336*	1.3041**	1.2940**
		t = 2.1130		t = 1.7492	t = 2.5222	t = 2.5039
Weekday	0.0307	−0.0373	0.0172	−0.0470	0.0275	0.0106
	t = 0.3211	t = −0.4029	t = 0.1777	t = −0.5052	t = 0.2709	t = 0.1075
Constant	−0.1042	−0.0167	−0.2723	−0.2390	−0.0689	0.1120
	t = −0.2789	t = −0.0462	t = −0.6399	t = −0.5600	t = −0.1741	t = 0.2800

Table 2 (continued)

Observations	461	461	461	461	459	459
Newey-West lags	7	2	6	2	2	1
Adjusted R^2	0.0117	0.1446	0.0078	0.1392	0.1262	0.1256

This table shows regression results from equation 3, using cryptocurrency futures returns with $c \in \{BTC, ETH\}$ for period t as the dependent variable. We employ two different sentiment measures (and their lags): $Sent_c^{Crypto}$ represents our crypto-weighted sentiment variable, and $Sent_c$ denotes the standard (Loughran & McDonald, 2011) sentiment approach. In columns (1)–(4), we extract sentiment from BTC-related articles, while in columns (5) and (6), we use ETH-related articles. The corresponding t-statistics are shown below. Newey-West lags and the Adjusted R^2 are reported upon. ***, **, * denote significance at the 1%, 5%, and 10% levels respectively

light that, unlike gold, Bitcoin generally behaves more like a risky asset than a safe haven. We also find a positive and significant coefficient for the $GDP\ surprise_t$, variable, which we interpret in a similar manner, as GDP captures broader trends in economic development.

Among the Bitcoin-specific variables, we observe a positive and significant coefficient of the $Irrational_{t,BTC}$ variable. This suggests that more irrational-optimistic sentiment is linked with higher BTC futures returns, consistent with theoretical expectations. Additionally, we observe a strong and statistically significant positive relationship between the returns of the Dow Jones Industrial Average and BTC futures returns. This finding aligns with Wang et al. (2020), who document a robust positive correlation between Bitcoin and the Dow Jones Index. Conversely, we identify a negative and significant relationship between the US Dollar Index and BTC futures returns. A strengthening US Dollar is thus associated with declining Bitcoin returns. One possible explanation is that the US Dollar gains value when the interest rate level (compared to other major economies) rises in the United States (Engel & West, 2010). Elevated interest rates tend to exert downward pressure on risky asset classes (Nissim & Penman, 2003). Given Bitcoin's speculative nature and its strong positive correlation with equity indices such as the Dow Jones, this may help explain the inverse relationship with the US Dollar Index (Wang et al., 2020). No significant relationship is found between the Fed Funds Rate and BTC futures returns.

4.1.2 ETH futures returns and ETH news sentiment relation

Similar to BTC futures, we also investigate the relation between ETH news sentiment and ETH futures returns. The results are shown in columns (5) and (6) in Table 2.

Regarding the aggregated daily ETH new sentiment ($Sent_{t,ETH}$) as well as crypto-weighted ETH news sentiment variables ($Sent_{t,ETH}^{Crypto}$), we can neither observe a strong and continuous contemporary relation nor a significant reverse effect in the lagged news coefficients. Even the $Irrational_{t,ETH}$ variable, which is solely based on ETH-related social media and news sentiment measures, does also show no significant coefficient. Consequently, the results do not provide empirical support for Hypothesis 1b. With regard to macroeconomic indicators, a consistent pattern emerges, similar to the findings in Bitcoin analyzes: Strong significance is observed particularly for the variables Dow Jones Industrial Average Index, US Dollar Index, as well as Capacity Utilisation surprise and GDP surprise.

4.2 Disaggregating news sentiment measures

Next, we examine whether cryptocurrency futures returns respond differently to positive and negative news sentiment (Hypothesis 2a/2b). We divide our crypto-weighted news sentiment into positive $(Sent_{t,c}^{Crypto})^{+}$ and negative $(Sent_{t,c}^{Crypto})^{-}$ values. Mathematically, let H(x) be a Heaviside function defined by

$$H(x) := \begin{cases} 1, & x > 0 \\ 0, & x \leq 0. \end{cases}$$

Then we define

$$(Sent_{t,c}^{Crypto})^{+} := Sent_{t,c}^{Crypto}\, H\left(Sent_{t,c}^{Crypto}\right),$$
$$(Sent_{t,c}^{Crypto})^{-} := Sent_{t,c}^{Crypto}\, H\left(-Sent_{t,c}^{Crypto}\right),$$

for a cryptocurrency $c \in \{BTC, ETH\}$.

4.2.1 BTC positive and negative news sentiment

Columns (1) and (2) of Table 3 present the results for BTC futures. Here, only the negative news sentiment $(Sent_{t,c}^{Crypto})^{-}$exhibit a significant relationship with BTC futures returns. Negative news sentiment is thus associated with declining futures returns. However, the insignificant *p*-value for the positive news variable displays an asymmetric response. All in all, there is only evidence that BTC futures returns react negatively to negative news. So the positive contemporary relationship between weighted news sentiments and Bitcoin returns observed in Section 4.1 may therefore primarily be driven by negative news sentiments. It should be noted, however, that in the dataset used, the majority of news items were classified as negative. In column (2), we add further control variables. The results of BTC-related controls are in line with previous findings, showing a positive and significant coefficient of $Irrational_{t,BTC}$ and $DJIA\ log\ return_t$, as well as negative and significant coefficient of the $USDI\ log\ return_t$ variable.

With respect to macroeconomic controls, we analyze the effects of both positive and negative market surprises, following the methodological approach of Smales (2014). These surprises are calculated as the difference between the actual released figures and the corresponding expectations derived from market surveys.

The positive market surprise, defined as a positive deviation of the actual Consumer Price Index (CPI) from its forecasted value, emerges as statistically significant. This finding implies that when inflation data exceeds expectations, indicating that surveyed forecasts underestimated actual inflation, there is a positive association with BTC futures returns, suggesting that higher-than-anticipated inflation is positively related to returns on BTC futures. A potential explanation for this relationship

Table 3 Disaggregating news: Relation between positive and negative news sentiment and cryptocurrency futures returns

	Dependent variable: $R_{t,c}$ with $c = BTC$		Dependent variable: $R_{t,c}$ with $c = ETH$	
	(1)	(2)	(3)	(4)
$(Sent_{t,c}^{Crypto})+$	−62.4192	−23.4963	92.2307**	63.2817*
	t = −1.1747	t = −0.4039	t = 2.4973	t = 1.7951
$(Sent_{t,c}^{Crypto})-$	26.3390**	24.7290**	5.2648	3.7544
	t = 2.0196	t = 1.9788	t = 0.3991	t = 0.3049
$R_{t-1,c}$	−0.0367	−0.0370	−0.0105	−0.0079
	t = −0.5188	t = −0.5202	t = −0.1949	t = −0.1353
$Irrational_{t,c}$		13.5496*		−1.0075
		t = 1.7477		t = −0.4047
$DJIA\ log\ return_t$		1.1691***		1.3595***
		t = 5.0698		t = 5.4959
$USDI\ log\ return_t$		−1.0084**		−1.2355**
		t = −2.3449		t = −2.2616
$FFR\ log\ return_t$		0.0733		0.0946
		t = 0.8207		t = 1.4271
$(CPI\ surprise_t)^+$		3.2183*		6.3053***
		t = 1.7590		t = 2.8975
$(CPI\ surprise_t)^-$		2.0290		3.5657
		t = 0.4978		t = 0.9098
$(PPI\ surprise_t)^+$		−0.2589		−0.5435
		t = −0.2215		t = −0.4333
$(PPI\ surprise_t)^-$		1.6983		1.0071
		t = 1.3327		t = 0.9171
$(CapUt\ surprise_t)^+$		4.2693***		3.3987***
		t = 3.6700		t = 3.2315
$(CapUt\ surprise_t)^-$		−2.9382***		−3.3149***
		t = −4.5915		t = −3.8319
$(PersIn\ surprise_t)^+$		−0.0142		−0.0976
		t = −0.0106		t = −0.0641
$(PersIn\ surprise_t)^-$		−0.4454		−0.1676
		t = −0.5170		t = −0.2152
$(UER\ surprise_t)^+$		−0.2496		−1.3872
		t = −0.2083		t = −0.9878
$(UER\ surprise_t)^-$		−1.1887		−0.6285
		t = −1.5079		t = −0.4955
$(GDP\ surprise_t)^+$		1.2464		1.3686**
		t = 1.6290		t = 2.3560
$(GDP\ surprise_t)^-$		−2.4639		−1.0014
		t = −1.1756		t = −0.3908
$Weekday$	0.0408	−0.0269	0.1089	0.0474
	t = 0.4161	t = −0.2601	t = 1.0462	t = 0.4341
$Constant$	0.4724	0.4740	−0.2777	−0.2580
	t = 1.4806	t = 1.4428	t = −0.8119	t = −0.6963

Table 3 (continued)

Observations	461	461	459	459
Newey-West lags	6	1	7	0
Adjusted R^2	0.0009	0.1207	0.0054	0.1282

The table presents regression results for the contemporaneous relationship between disaggregated crypto-weighted news sentiment and cryptocurrency futures returns. In columns (1) and (2), we extract sentiment from BTC-related articles, while in columns (3) and (4), we use ETH-related articles. The corresponding t-statistics are shown below. Newey-West lags and the Adjusted R^2 are reported upon. ***, **, * denote significance at the 1%, 5%, and 10% levels respectively

is that heightened inflation may raise concerns regarding the depreciation of fiat currencies, thereby increasing demand for alternative assets such as Bitcoin.

Furthermore, both the positive and negative surprise variables for the Capacity Utilization control variable are statistically significant. This suggests that deviations in utilization rates, either above or below expectations, may signal shifts in economic activity. Increases (decreases) in utilization could reflect economic expansion (contraction), potentially creating a more supportive (adverse) environment for riskier asset classes, as discussed in Nissim and Penman (2003). In contrast, the remaining macroeconomic control variables do not exhibit statistically significant effects.

Taken together, while the results do not entirely confirm Hypothesis 2a, they offer partial support by indicating that there is a significant relationship between BTC futures returns and negative crypto news sentiment.

4.2.2 ETH positive and negative news sentiment

Splitting ETH related sentiment variables into positive and negative news (see columns (3) and (4) of Table 3), we detect a positive and significant relationship between positive ETH news and ETH futures returns, while negative news variables remain insignificant. Thus, although we cannot find any significant relation between contemporary news sentiment and ETH futures returns, we observe a significant relation when separately examining positive news. However, such positive news is relatively rare (more than 75% of the aggregated news sentiments are negative), so the observed aggregate effect is zero. One possible explanation may be that Ether is primarily valued for its platform, enabling decentralized applications and smart contracts. Positive advancements or news about new projects and applications on the Ethereum platform may bolster investor confidence and drive up ETH futures prices. Overall, although the regression results do not fully confirm Hypothesis 2b, they offer partial support by indicating a significant relationship between ETH futures returns and positive crypto-specific ETH news sentiment.

4.3 The linkage between net trader positions and news sentiment

In this section, we explore a potential relationship between the net trading positions of cryptocurrency-related speculators and hedgers and crypto news sentiment. Given that CFTC reports are published every week, we calculate the weekly sentiments using an exponential moving average approach, defined by

$$EMA_t := \begin{cases} S_1, & \text{if } t = 1 \\ \alpha S_t + (1-\alpha)\cdot EMA_{t-1}, & \text{if } t > 1. \end{cases}$$

In this model, α displays the smoothing factor and S_t denotes the respective sentiment variable at time t

4.3.1 BTC net trader positions and BTC news sentiment

The regression results are presented in columns (1)–(4) of Table 4. A significant and positive relationship is observed between hedgers' net positions (column 1) and Bitcoin-specific news sentiment, so hedgers expand their long positions as news sentiment increases. An explanation may be that high sentiment values often coincide with over-optimism (Stambaugh et al., 2012). Given the nature of hedgers, they may seek to hedge at a high level, prompting increased demand for long positions.

Column (2) shows the regression results when analyzing the speculators' net positions as the dependent variable. Bitcoin-specific news sentiment exhibits a highly significant and negative relationship (at the 1% level) with speculators' positions. The negative coefficient suggests that speculators increase their short positions (reduce their long positions) during periods of very positive market sentiment. One possible explanation for this behavior is also that phases of high market sentiment lead to over-optimism and mispricing in the stock market (Stambaugh et al., 2012). Since both stock and cryptocurrency markets are considered sentiment-driven, similar mispricings could be observed in the Bitcoin market (Akyildirim et al., 2021; Chau et al., 2016). Speculators may anticipate these anomalies, resulting in increased short positions during such periods.

Overall, since the relation between news sentiment and hedgers' and speculators' positions shows opposite signs, this suggests that speculators increase their short positions as hedgers expand their long positions. This is consistent with the fact that speculators and hedgers provide liquidity to each other in futures markets (Kang et al., 2020). In Columns (3) and (4) we add further control variales. While $Irrational_{t,BTC}$ does only show one significant coefficent at 10% level, further significant coefficients in the expected directions can be observed for the BTC futures returns. In summary, the results support Hypothesis 3a, indicating a significant relation between the net positions of speculators and hedgers and news sentiment.[16]

4.3.2 ETH net trader positions and ETH news sentiment

Next, we examine a potential linkage between net trading positions of speculators and hedgers and ETH-specific news sentiment. Again, we use an exponential moving average approach to transform the daily crypto-intensity weighted ETH news sentiments into weekly news sentiments. The results are shown in columns (5)–(8) of Table 4.

[16] As a robustness check, we construct weekly sentiment by simply averaging daily scores. Appendix Table 8 shows that the results are qualitatively unchanged.

Table 4 Relation between net trading positions and weekly crypto-weighted news sentiment (EMA $Sent_{t,c}^{Crypto}$)

	Net trading positions with c = BTC				Net trading positions with c = ETH			
	$Hedgers_{BTC}$	$Speculators_{BTC}$	$Hedgers_{BTC}$	$Speculators_{BTC}$	$Hedgers_{ETH}$	$Speculators_{ETH}$	$Hedgers_{ETH}$	$Speculators_{ETH}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMA $Sent_{t,c}^{Crypto}$	2.3125***	−2.3353***	2.4217***	−2.4734***	1.4591	−3.2212*	0.2652	−1.5240
	t = 3.4851	t = −3.2104	t = 3.3877	t = −3.1528	t = 1.1198	t = −1.8767	t = 0.2253	t = −0.9228
$R_{t,c}$*(rolling)*	0.0010*	−0.0013**	0.0011**	−0.0015***	0.0030***	−0.0037***	0.0026***	−0.0031***
	t = 1.7326	t = −2.2824	t = 2.1449	t = −2.9036	t = 3.2431	t = −3.0135	t = 2.9001	t = −2.7802
EMA Irrational$_{t,c}$			−0.4752	0.4711			−1.1860***	1.6207***
			t = −1.5907	t = 1.5142			t = −3.4362	t = 3.8528
DJIA (rolling)			0.0050	−0.0056			−0.0021	−0.0015
			t = 1.4391	t = −1.5483			t = −0.3109	t = −0.1696
USDI (rolling)			−0.0043	0.0054			−0.0124	0.0142
			t = −0.5350	t = 0.6150			t = −0.8602	t = 0.7280
FFR (rolling)			−0.0001	−0.0002			−0.0016	−0.0010
			t = −0.0919	t = −0.1603			t = −0.6569	t = −0.3207
Constant	0.0203**	−0.0522***	0.0190**	−0.0509***	0.0094	−0.0998***	0.0141	−0.1028***
	t = 2.3259	t = −5.0736	t = 2.2509	t = −5.0500	t = 0.6343	t = −4.7805	t = 1.0272	t = −5.2596
Observations	95	95	95	95	94	94	94	94
Newey-West-lags	2	2	3	2	0	2	1	3
Adjusted R^2	0.1736	0.1725	0.1953	0.1966	0.0665	0.0938	0.2007	0.2588

The table presents regression results for the relationship between hedgers' and speculators' cryptocurrency futures net trading positions as the dependent variable and weekly crypto-weighted sentiment (EMA $Sent_{t,c}^{Crypto}$) described in sect. 4.3 with $\alpha = \frac{1}{2}$. In columns (1)–(4), we extract sentiment from BTC-related articles, while in columns (5)–(8), we use ETH-related articles. The corresponding t-statistics are shown below. Newey-West lags and the Adjusted R^2 are reported upon. ***, **, * denote significance at the 1%, 5%, and 10% levels respectively

In line with previous findings in the context of ETH news sentiment, we find no ongoing evidence for a significant relation between the hedger's ETH net positions and ETH news sentiments and also for a negative and significant relation between the speculator's ETH net positions and ETH news sentiment. Thus, Hypothesis 3b cannot be confirmed based on the presented results.

5 Robustness

5.1 News sentiment during different market phases

Prior studies examined the question of whether cryptocurrencies in general can act as a safe haven asset to effectively hedge against equity market crises. Some authors claim that cryptocurrencies, although highly correlated with each other, are disconnected or isolated from traditional financial assets (see e.g., Corbet et al. 2018). In its early life cycle, Bouri et al. (2017) shows that bitcoin acted as a hedge before the Bitcoin-US dollar price crash of 2012. However, Smales (2019), Bouri et al. (2017), and Shahzad et al. (2019) claim that Bitcoin no longer fulfills these properties. While the classification of cryptocurrencies as safe havens remains debatable, market cycles can, nevertheless, moderate investor responses to news sentiment.

Although our sentiment measures capture rational information processing, investor behavior is likely to be further shaped by broader current market sentiment. In recent years, the cryptocurrency market has repeatedly been hit by dramatic events. These range from highly negative developments, such as the collapse of FTX, to more positively perceived ones, such as the potential introduction of a Bitcoin ETF. It is therefore essential to account for extraordinary market uncertainty that are specific to the crypto sector. Market uncertainty prompts investors to seek stability, leading to a shift of capital from high-risk assets to more secure and reliable investments (Burggraf et al., 2021). Even if cryptocurrencies do not consistently hedge against market phases of financial distress, they remain speculative assets whose sensitivity to information may alter based on investor mood and risk tolerance. In optimistic market phases, characterized by positive momentum, sudden negative news contradicting positive expectations can cause a price correction. In contrast, in pessimistic market phases, positive news may receive more attention and generate stronger upward price adjustments due to the relative absence of positive signals. These asymmetries suggest that the marginal effect of sentiment on returns may vary depending on the prevailing market sentiment.

So as a further robustness test, we examine whether, and if so to what extent, the relationship between news sentiments and futures returns relies on market phases and, in particular, in times of optimism or pessimism and recession on crypto markets. To identify these cycles, we use the *Crypto Fear and Greed Index*, which ranges from 0 (extreme fear) to 100 (extreme greed) and displays the overall crypto market sentiment. We define a recession dummy variable ($D_{Recession}$) equal to one if the daily *Crypto Fear and Greed Index* underscores the previous 365 days rolling median, and zero otherwise. The results of BTC futures are displayed in columnes (1) and (2) of Table 5, while column (3) shows the results for ETH futures. However, since the interaction term between the news sentiment and $D_{Recession}$ does not show any significant values, we cannot find evidence for changing relations in times of market recessions.

Overall, our results indicate that the relationship between news sentiment and cryptocurrency futures returns remains robust across different market conditions. This suggests that professional investors in the futures market integrate sentiment into their trading strategies consistently, regardless of prevailing risk sentiment or macroeconomic uncertainty. Unlike retail-driven spot markets, where sentiment-driven price reactions may be amplified by speculative behavior, the futures market appears to process news sentiment more systematically and rationally, maintaining stable across both bullish and bearish phases.

5.2 Waterfall-effect of BTC on ETH

Gemici and Polat (2021) claim that Bitcoin volatility has a direct spillover on other cryptocurrencies and in particular Ether. However, there is no observable reverse effect of Ether on Bitcoin (Gemici & Polat, 2021). Ciaian and Rajcaniova (2018) examine price relationships across a broader set of cryptocurrencies and find that Ether prices are affected by Bitcoin prices. Even Anamika and Subramaniam (2023) find that the sentiment surrounding the dominant cryptocurrency, i.e., Bitcoin, has an impact on the prices of other cryptocurrencies, which can be described as a "waterfall" effect. In turn, BTC news sentiment may therefore also be related to ETH futures returns. As a further robustness test, we therefore use BTC news sentiment to investigate a potential relationship with ETH futures returns. The results are shown in Table 6.

In contrast to the findings when analyzing the relationship between ETH news sentiment and ETH futures returns, the contemporary BTC sentiment variable shows a positive and significant effect. Even the irrational BTC variable exhibits a positive and significant coefficient. The results show supporting evidence that BTC news sentiment in particular exhibits a significant relationship with ETH futures returns. From an investor perspective, this makes it clear that bitcoin-specific news sentiment plays a crucial role in the area of ETH futures returns. All in all, we conclude that we can find evidence for a waterfall effect regarding BTC news sentiment.

6 Conclusion

This study provides new insights into the role of news sentiment in cryptocurrency futures markets, demonstrating its impact on BTC and ETH futures returns as well as net trading positions of professional market participants. Unlike traditional financial assets, cryptocurrencies lack fundamental valuation metrics (Aysan et al., 2024), making rational sentiment a crucial tool for understanding price formation and institutional trading behavior.

One of our key contributions is the enhancement of traditional sentiment analysis. By constructing a crypto-specific dictionary and incorporating a crypto density weight (CDW), we address a major limitation of standard dictionary-based

Table 5 News sentiment and cryptocurrency futures returns for different crypto market phases

	Dependent variable: $R_{t,c}$ with c = BTC		Dependent variable: $R_{t,c}$ with c = ETH
	(1)	(2)	(3)
$Sent_{t,c}^{Crypto} * D_{Recession}$	−23.0436	−24.6418	6.7487
	t = −1.1284	t = −1.4190	t = 0.3640
$Sent_{t,c}^{Crypto}$	24.6185*	26.4936**	12.7787
	t = 1.8982	t = 2.1977	t = 1.1436
$Irrational_{t,c}$		14.1342*	−0.2805
		t = 1.8494	t = −0.1175
$R_{t-1,c}$	−0.0275	−0.0270	−0.0067
	t = −0.3808	t = −0.3908	t = −0.1212
DJIA log return$_t$		1.1357***	1.3635***
		t = 4.8805	t = 5.3715
USDI log return$_t$		−1.0483**	−1.3851***
		t = −2.4803	t = −2.6350
FFR log return$_t$		0.0526	0.0941
		t = 0.7555	t = 1.4559
CPI surprise$_t$		−0.1212	0.4375
		t = −0.0423	t = 0.1217
PPI surprise$_t$		−1.2632	−0.7933
		t = −1.4368	t = −1.0017
CapUt surprise$_t$		3.5435***	3.4108***
		t = 4.8163	t = 5.4344
PersIn surprise$_t$		0.1292	−0.0192
		t = 0.1447	t = −0.0192
UER surprise$_t$		0.4522	−0.0463
		t = 0.5614	t = −0.0425
GDP surprise$_t$		1.4281*	1.2307**
		t = 1.9193	t = 2.1506
Weekday	0.0306	−0.0375	0.0267
	t = 0.3126	t = −0.3956	t = 0.2616
Constant	0.3341	0.4605	0.0097
	t = 1.1149	t = 1.5684	t = 0.0304
Observations	461	461	459
Newey-West lags	5	3	2
Adjusted R^2	0.0014	0.1299	0.1268

This table shows the regression results between news sentiment and BTC futures returns as the dependent variable in (1) and (2), as well as between news sentiment and ETH futures returns as the dependent variable in (3). Based on the Fear and Creed Index, $D_{Recession}$ is a dummy variable equal to one if the crypto market exhibits phases of pessimism and crisis. The corresponding t-statistics are shown below. Newey-West lags and the Adjusted R^2 are reported upon. ***, **, * denote significance at the 1%, 5%, and 10% levels respectively

approaches (Calomiris & Mamaysky, 2019). This refined methodology allows for a more precise identification of crypto-relevant content and provides a replicable framework for real-time sentiment analysis in financial markets.

By aggregating more than 9,100 BTC-related and 5,400 ETH-related individual news articles on a daily basis, we show that crypto-weighted news sentiment is significantly related to futures returns. In particular, we find a significant contemporane-

Table 6 The Relationship between BTC news sentiment and ETH futures returns

	Dependent variable: $R_{t,c}$ with c = ETH
$Sent^{Crypto}_{t,BTC}$	21.2378*
	t = 1.8294
$Sent^{Crypto}_{t-1,BTC}$	7.7957
	t = 0.5335
$Sent^{Crypto}_{t-2,BTC}$	−14.1932
	t = −1.2964
$Sent^{Crypto}_{t-3,BTC}$	−23.7660
	t = −1.2791
$Irrational_{t,BTC}$	15.7075*
	t = 1.9166
$R_{t-1,ETH}$	−0.0819
	t = −1.4171
DJIA log return$_t$	1.3372***
	t = 5.1306
USDI log return$_t$	−1.5091***
	t = −3.0171
FFR log return$_t$	0.0637
	t = 1.0275
CPI surprise$_t$	1.1409
	t = 0.3417
PPI surprise$_t$	−0.6566
	t = −0.9736
CapUt surprise$_t$	3.3215***
	t = 5.2052
PersIn surprise$_t$	0.1916
	t = 0.1816
UER surprise$_t$	−0.3375
	t = −0.3224
GDP surprise$_t$	1.1322
	t = 1.4216
Weekday	−0.0041
	t = −0.0408
Constant	−0.1689
	t = −0.3880
Observations	458
Newey-West-lags	1
Adjusted R^2	0.1469

The table presents regression results for the relationship between BTC news sentiment and ETH futures returns as the dependent variable. Crypto-weighted sentiment ($Sent^{Crypto}$), which is based on BTC-related news, is used as the sentiment variable. The corresponding t-statistics are shown below. Newey-West lags and the Adjusted R^2 are reported upon. ***, **, * denote significance at the 1%, 5%, and 10% levels respectively ous relation between BTC crypto-weighted news sentiment and BTC futures returns. The results also reveal that this effect is mostly driven by negative news, since negative crypto-weighted news sentiment is related with significant negative market reactions, whereas positive news sentiment shows no measurable effect. Furthermore, professional investors adjust their positions accordingly: hedgers increase long positions during periods of positive sentiment, while speculators take on more short positions. In the case of ETH futures, we solely identify a significant positive relationship between positive crypto-weighted ETH-news sentiment and futures returns.

Our results present evidence that the relation between news sentiment and BTC and ETH futures returns remains stable across market conditions. Even during periods of heightened uncertainty in the crypto market (proxied by the *Fear and Greed Index*), sentiment-driven relationships do not change. This suggests that professional market participants integrate rational sentiment consistently, unlike retail-driven spot markets, where speculative behavior or irrational sentiment can amplify price reactions, momentum effects (Liu & Tsyvinski, 2021) or herding behavior (Celeste et al., 2020; Gama et al., 2019).

Additionally, we uncover a news spillover effect, as BTC-related news sentiment has a stronger impact on ETH futures than ETH-specific news itself. This emphasizes that Bitcoin retains a dominant informational role in the broader cryptocurrency market, shaping expectations and trading behavior across cryptocurrency assets and underlines the uncovered substantial differences between the analyses of BTC and ETH futures.

Nevertheless, our study has some limitations. Although the crypto-density weight and GenAI-assisted crypto lexicon enhance topical relevance, our sentiment proxy remains a dictionary-based, bag-of-words construct that can potentially misclassify tone or fail to detect negation and context reliably. Future research may employ advanced machine learning techniques, e.g. topic modeling, and other AI tools to better capture context or inter-news relationship. We also aggregate sentiment on a daily basis and implicitly treat news as exogenous to same-day futures returns. In this context, an intraday analyses may be particularly fruitful to better uncover the news-price lead-lag. Additionally, the proposed density-weighting approach may be extended to other futures markets.

Our findings have important implications for institutional investors, risk managers, and policy-makers. For professional market participants, understanding the influence of rational news sentiment can improve trading strategies and risk management in cryptocurrency derivatives markets. For policymakers, our results underscore the importance of monitoring sentiment-driven volatility and its potential effects on market stability.

Appendix

Table 7 presents the terms included in the crypto-specific dictionary, and Figure 1 illustrates the 15 most frequently occurring terms in BTC-related articles based on their relative frequency.

Table 7 Crypto-specific dictionary

Category	Term list
General	Bitcoin, BTC, ethereum, ETH, Ripple, Satoshi, Satoshi Nakamoto, shitcoin, Tether, XRP
Scarcity	Bitcoin whale, diamond hands, digital currency, flash sale, halving, halving event, HODL, hodler, paper hands, price manipulation, whale dump, whale trade, whale wallet
Network value	Aave, Armstrong, Bankman-Fried, Binance, Bitmain, Blockstream, Buterin, Cardano, Chainlink, Coinbase, Coinmarket, crypto arbitrage, crypto exchange, defi yield, FOMO, fomo, FOMO investor, FUD, fudder, FTX, Gensler, Hoskinson, Kraken, liquidity pool, MakerDAO, MicroStrategy, Musk, Peirce, Polkadot, pump, pump and dump, Ripple Labs, SBF, stable yield farming, Uniswap, Winklevoss, Wood, Zhao
Security	Cold staking, DAO, decentralization, decentralized, decentralized autonomous organization, decentralized exchange, defi, defi exchange, DLT, distributed ledger, distributed ledger technology, ledger, PoS, PoW, private key, proof of stake, proof of work, public key, staking, staking pool, validator, wallet, wallet address
Utility	Bitcoin ETF, block, blockchain, block size, CBDC, central bank digital currency, chain migration, crypto, crypto asset management, crypto assets, crypto-centric, crypto derivatives, crypto ETF, crypto hedge fund, cryptocurrency, crypto swap, fee structure, fiat on-ramp, fork, gas fee, gas limit, gas war, genesis block, governance token, ICO, initial coin offering, layer 1, layer 2, layer 2 solution, network fees, NFT, non-fungible token, off-chain, on-chain, security token offering, smart contracts, stablecoin, STO, token, tokenized asset, utility token
Cost of production	Crypto mining farm, hash power, hash rate, mining, network difficulty

This table presents the terms within our crypto-specific dictionary

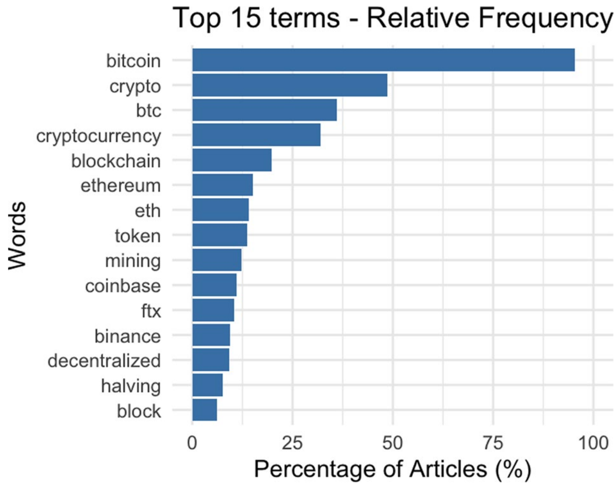

Fig. 1 Top 15 terms by relative frequency in BTC articles

Table 8 reports a robustness check using the mean value of sentiment.

Table 8 Relation between net trading positions and weekly crypto-weighted news sentiment (Mean $Sent_{t,c}^{Crypto}$)

	Net trading positions with c = BTC				*Net trading positions with c = ETH*			
	$Hedgers_c$	$Speculators_c$	$Hedgers_c$	$Speculators_c$	$Hedgers_c$	$Speculators_c$	$Hedgers_c$	$Speculators_c$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean $Sent_{t,c}^{Crypto}$	2.4869***	−2.4840***	2.5464***	−2.5361***	0.7818*	−1.3214**	0.4213	−0.7715
	t = 4.4543	t = −4.2284	t = 3.9014	t = −3.4939	t = 1.8847	t = −2.4785	t = 1.1681	t = −1.5889
$R_{t,c}$ *(rolling)*	0.0013**	−0.0016***	0.0016***	−0.0020***	0.0026***	−0.0032***	0.0026***	−0.0032***
	t = 2.2267	t = −2.7195	t = 2.9251	t = −3.5954	t = 2.8711	t = −2.7457	t = 3.0919	t = −3.1112
Mean $Irrational_{t,c}$			−0.5926**	0.5934**			−0.9297***	1.2982***
			t = −2.1433	t = 2.0670			t = −3.5078	t = 4.0155
$DJIA_{(rolling)}$			0.0062*	−0.0070**			−0.0034	0.0002
			t = 1.9347	t = −2.0697			t = −0.4985	t = 0.0275
$USDI_{(rolling)}$			−0.0037	0.0041			−0.0155	0.0173
			t = −0.4824	t = 0.4841			t = −1.0013	t = 0.8256
$FFR_{(rolling)}$			−0.0010	0.0006			−0.0015	−0.0009
			t = −0.7377	t = 0.3794			t = −0.6123	t = −0.2711
Constant	0.0218***	−0.0533***	0.0196**	−0.0505***	0.0294*	−0.1254***	0.0264	−0.1164***
	t = 2.9031	t = −6.3716	t = 2.4598	t = −5.3184	t = 1.8789	t = −5.8210	t = 1.6600	t = −5.3144
Observations	95	95	95	95	94	94	94	94
Newey-West-lags	1	1	1	2	1	2	3	4
Adjusted R^2	0.1912	0.1871	0.2523	0.2470	0.1000	0.1377	0.1967	0.2623

The table presents regression results for the relationship between hedgers' and speculators' cryptocurrency futures net trading positions as the dependent variable and weekly crypto-weighted sentiment (Mean $Sent_{t,c}^{Crypto}$). In columns (1)–(4), we extract sentiment from BTC-related articles, while in columns (5)–(8), we use ETH-related articles. The corresponding t-statistics are shown below. Newey-West lags and the Adjusted R^2 are reported upon. ***, **, * denote significance at the 1%, 5%, and 10% levels respectively

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Declarations

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