Journal of International Money and Finance 157 (2025) 103394

Contents lists available at ScienceDirect

Journal of International Money and Finance

journal homepage: www.elsevier.com/locate/jimf

Listening to the Market: Music sentiment and cryptocurrency returns[☆]

Sinda Hadhri[a,b], Mehak Younus[c], Muhammad Abubakr Naeem[d,*], Larisa Yarovaya[e]

[a] UCLy (Lyon Catholic University), ESDES, Lyon, France
[b] UR CONFLUENCE: Sciences & Humanités (EA 1598), Lyon, France
[c] Shaheed Zulfikar Ali Bhutto Institute of Science and Technology (SZABIST) - Department of Management Sciences, Pakistan
[d] Economics and Finance Department, College of Business and Economics, United Arab Emirates University, United Arab Emirates
[e] The Centre for Digital Finance, Southampton Business School, United Kingdom

ARTICLE INFO

JEL classification:
G11
G12
G14

Keywords:
Music sentiment
Spotify
Investor mood
Cross-section of cryptocurrency returns
Return predictability

ABSTRACT

This paper investigates how investor sentiment, captured through a novel Spotify-based mood metric, influences the cross-sectional pricing of cryptocurrencies. Drawing on behavioral finance and psychological theories, we hypothesize that emotional states reflected in musical choices influence cryptocurrency returns. Using weekly data from 2,551 cryptocurrencies over five years, we find that sensitivity to music sentiment significantly predicts future returns. Our results reveal a negative relationship between music sentiment beta and near-term returns, with multivariate regressions confirming its explanatory power beyond traditional risk factors. We also uncover nonlinear and time-varying effects, consistent with sentiment-driven mispricing and investor attention cycles. This study offers a global sentiment measure, contributing to the understanding of mood-driven dynamics in speculative markets and informing trading strategies, policy, and research.

1. Introduction

The interplay between investor sentiment and asset classes has been a focal point of behavioral finance research. Psychological evidence suggests that positive (negative) sentiment causes investors to focus on positive (negative) information (Isen et al., 1978). According to Schwarz and Clore's (1983) mood-as-information theory, people use their emotional state to assess risk and make decisions when information is lacking. In financial markets, sentiment significantly predicts returns (e.g., Baker and Wurgler, 2007; Huang et al., 2014). Kaplanski et al. (2013) found that general feelings impact predictions, and investors with seasonal effective disorder have lower return expectations and perceive higher risks. Baker and Wurgler (2006) showed that sentiment changes affect stock prices, especially speculative stocks, and that decreased sentiment can drive investors towards safer stocks.

With the rapid expansion of cryptocurrency markets, understanding the influence of sentiment on these assets has become increasingly pertinent. Previous research has examined various aspects of cryptocurrencies, including its stylized features (Chiu and Koeppl, 2019; Härdle et al., 2020), pricing determinants (Bori and Shakhnov, 2021; Liu et al., 2022; Biais et al., 2023; Karau, 2023),

☆ This article is part of a special issue entitled: 'Cryptocurrency' published in Journal of International Money and Finance.

* Corresponding author.
E-mail addresses: shadhri@univ-catholyon.fr (S. Hadhri), mehakyounus@gmail.com (M. Younus), muhammad.naeem@uaeu.ac.ae (M.A. Naeem), l.yarovaya@soton.ac.uk (L. Yarovaya).

https://doi.org/10.1016/j.jimonfin.2025.103394

Available online 18 July 2025

volatility (Hafner, 2018; Hansen et al., 2022), liquidity (Trimborn et al., 2019; Bianchi et al., 2022; Farag et al, 2025), arbitrage opportunities (Hautsch et al., 2024; Makarov and Schoar, 2020), and investor behavior (Yao et al., 2021; Dhawan and Putniņš, 2022; Hackethal et al., 2021; Cai and Zhao, 2024; Naeem et al., 2021a, 2021b).

For instance, Cong et al. (2021) developed a theoretical model of token markets, demonstrating that token value is largely driven by users' endogenous activities, which play a crucial role in explaining the cross-section of returns. These activities are likely influenced by market sentiment. In line with this, Liu and Tsyvinski (2021) highlight the significance of investor sentiment in driving cryptocurrency market dynamics. Sockin and Xiong (2023) further emphasize that, due to the difficulty in assessing fundamental values, cryptocurrency investors often rely heavily on sentiment to form their value assessments.

As the cryptocurrency market is heavily reliant on online platforms, investors tend to gather data and insights primarily from internet sources like web searches, forums, and social media. Studies have found that factors such as Google Trends attention (Urquhart, 2018), Google Trends sentiment (Liu and Tsyvinski, 2021), Twitter sentiment (Kraaijeveld and Smedt, 2020), and forum engagement (Dias et al., 2022), are significant predictors of cryptocurrency market movements. The 'social' aspect of cryptocurrencies is also highlighted by Lucey et al. (2022), who introduced news-based cryptocurrency uncertainty indexes that incorporate not only traditional media coverage but also alternative and social media sources. This online-centric nature of the market makes sentiment a critical factor in understanding cryptocurrency price dynamics.

While scholars' attention has been focused on extracting investment sentiment from various online media sources, indirect indicators reflecting investor mood have been largely neglected in cryptocurrency research (Hadhri, 2023). Spotify trends can serve as a powerful proxy for investors' emotional states, as the music people listen to often reflects their mood. Sudden increases in the popularity of certain music genres may be linked to broader economic anxiety, geopolitical events, and, ultimately, may influence investors' decision-making. To address this gap in the literature, i we propose leveraging recent developments in mood measurement by using a metric based on the songs individuals listen to. Specifically, we examine the cross-sectional predictability of cryptocurrency returns to test whether psychological theories on the emotional impact of music apply to behavioral finance. We draw on two strands of psychology literature. The first strand is music psychology, which examines the relationship between music and emotions. Research in this field has established a strong connection between music choices and mood states (Clynes, 1977; Rentfrow and Gosling, 2003; Lim and Park, 2018). Gabrielsson and Juslin (1996) found that nonverbal emotions in music significantly affect listeners' psychological dimensions. Juslin and Laukka (2004) discovered that adults engage with music primarily to experience and regulate emotions.

The second strand relates to psychological dimensions as measures of mood, focusing on two alternative mood states: "positive affect" and "negative affect" (Garland et al., 2010). Positive affect refers to the propensity to experience positive moods, encompassing feelings such as happiness, excitement, strength, inspiration, success, and determination. It also reflects how individuals positively interact with others and face life challenges. Negative affect, on the other hand, refers to the tendency to experience negative emotions and negativity in interactions and decisions, including feelings such as fear, nervousness, shame, upset, depression, and guilt. These two dimensions are largely independent; high negative affect indicates the presence of negative emotions, not the absence of positive ones, and vice versa. Psychologists have demonstrated that both states significantly impact human behavior (Garland et al., 2010).

Several studies have explored the use of music as a basis for measuring mood. Sabouni (2018) developed a music sentiment index based on Billboard Hot 100 data, showing that music sentiment can predict monthly returns on the Dow Jones, Nasdaq, and S&P 500. Similarly, Fernandez-Perez et al. (2020) and Edmans et al. (2022) used Spotify data and song valence to gauge investor mood in the stock market. Hadhri (2023) investigated the impact of music sentiment on cryptocurrency trading activity. Analysing the 20 largest cryptocurrencies by market capitalization, the study found that music sentiment is negatively and significantly correlated with both contemporaneous trading volume and price volatility.

Our research also leverages Spotify data—the leading global music streaming platform—to create a mood proxy for the cryptocurrency market. This approach is especially relevant given the overlap in demographics between Spotify users and cryptocurrency investors. With many cryptocurrency traders being young, tech-savvy individual investors, Spotify's user base aligns well with this group (Yelowitz and Wilson, 2015; Kaiser and Stöckl, 2020; Colombo and Yarovaya, 2024). We construct our mood indicator using the daily top-200 songs by global streaming numbers, offering a novel and pertinent sentiment measure for cryptocurrency stock returns. Specifically, while prior studies have explored the relationship between music sentiment and financial markets, our paper is among the first to examine this effect specifically in the context of a broad and dynamic cross-section of cryptocurrencies.

Our sample spans from February 24, 2018, to May 31, 2023, using weekly data on 2,551 cryptocurrencies. Focusing on the cross-section of cryptocurrency returns is particularly relevant in shedding light on the role that cryptocurrency-specific factors (e.g., the common risk factors of Liu et al., 2022) play in moderating or amplifying sentiment effects, which is crucial for market microstructure research, the development of trading strategies, and risk management practices.

Our study makes four key contributions to the literature. First, it advances the literature on investor sentiment's impact on cryptocurrency markets by employing a globally applicable sentiment detector based on collective music preferences. Unlike textual-based sentiment measures such as those derived from news articles, tweets, or other social-media posts, which may suffer from geographical constraints, language or cultural biases, our music sentiment index is universally interpretable and less subject to linguistic or regional heterogeneity. This allows us to capture more diffuse, ineffable emotional trends that may affect investor mood on a global scale. Second, unlike prior studies (e.g., Edmans et al., 2022; Fernandez-Perez et al., 2020; Kostopoulos and Meyer, 2018) that have explored music sentiment in relation to traditional asset classes, our paper is the first to explore its predictive power for a broad cross-section of cryptocurrencies. By applying music-based sentiment to a unique asset class that is decentralized, highly speculative, and sentiment-driven, we extend this literature and provide a rich testing ground for behavioral finance theories. Third, our paper contributes methodologically to the literature by introducing a dynamic and novel sentiment beta β^{MSI} that captures sensitivity of collective music sentiment, offering a discrete, high-frequency, and continuously available measure compared to event-based or survey-based indices. Unlike other conventional and existing sentiment indices that are updated infrequently or only around major events, our measure is constantly available, which enables finer-grained analysis of return predictability. Finally, our findings support the psychological theory linking mood to financial decision-making. By demonstrating that music-guided emotions have a significant impact on cryptocurrency returns, we reinforce previously developed hypotheses on music's impact are applicable to behavioral finance, especially in sentiment-sensitive markets like cryptocurrencies. The findings help bridge the gap between psychology and finance by proving that the impact of music sentiment on asset pricing extends beyond traditional markets.

Our analysis provides valuable insights for academics, practitioners, and policymakers alike. The cryptocurrency market, characterized by its speculative nature, offers a unique opportunity to study the behavior of assets with limited intrinsic value. Academic researchers such as Cheah and Fry (2015), Buffett (2018), and Bindseil and Schaaf (2024), have argued that Bitcoin and other cryptocurrencies lack intrinsic value, suggesting that their fundamental value is close to zero. This lack of intrinsic value makes cryptocurrencies an ideal context for studying the impact of sentiment on asset prices. For academics, the study of sentiment in such a volatile market can yield deeper insights into behavioral finance and investor psychology. Cryptocurrencies, being highly speculative, offer a clearer view of how sentiment—rather than fundamentals—can drive price movements, thereby enriching the theoretical understanding of market behavior in the absence of traditional value drivers.

From a practitioner's perspective, understanding the influence of sentiment on cryptocurrency prices can aid in the development of innovative financial products and investment strategies. Additionally, financial firms can design tailored products that manage exposure to sentiment risk, offering clients alternative ways to navigate the cryptocurrency market's volatility. For policymakers, the growing importance and size of the cryptocurrency market presents new challenges for financial stability. Sudden shifts in sentiment can lead to extreme price swings, which may have spillover effects on broader financial markets. Understanding how sentiment influences speculative assets like cryptocurrencies could inform regulatory frameworks aimed at reducing the risk of market bubbles and ensuring a more stable financial environment.

The reminder of the paper is structured as follows. The literature review and research gap are reported in Section 2. The data and methodology are described in Section 3. The results are presented in section 4. Section 5 concludes the study.

2. Theoretical background

2.1. Music psychology

There are several strands in the literature that inform our work. This first area of research relates to music psychology, a field that explores the connection between music and emotions. Clynes (1980), a prominent researcher in both neurophysiology and music, posits that music acts as a powerful stimulus that can deeply influence an individual's mood and behavior. The more aligned the music is with the emotional state of an individual, the more effectively these emotions are triggered. His work laid the foundation for subsequent studies that documented the strong relationship between music preferences and mood states (e.g., Greenberg et al., 2015; Rentfrow and Gosling, 2003). For instance, Gabrielsson and Juslin (1996) highlighted the significant influence of nonverbal emotions in music on listeners' psychological experiences, showing that music impacts various emotional dimensions. Lim and Park (2018) explored the relationship between arousal and cognitive performance following various musical activities, such as listening, singing, or playing an instrument. They discovered that although musical activities influenced arousal levels, this did not have a direct effect on memory recall. Instead, their findings suggest that the degree to which individuals enjoy the musical experience plays a key role in shaping their arousal levels. Greenberg et al. (2016) further demonstrated that music preferences are closely linked to personality traits, beyond basic demographic factors. Juslin and Laukka (2004) also found that one of the primary reasons adults engage with music is to experience and regulate emotions.

Psychological studies have expanded on this foundation, showing that emotions evoked by music are not solely a result of music's emotional positivity, but can also emerge from the activation of several interconnected systems. These systems include physiological changes (such as endocrine responses), motor activities (like dancing, singing, or clapping), and attentional shifts (e.g., Koelsch, 2014; Vuilermier and Trost, 2015). For example, even for genres traditionally associated with intense or negative emotions, like heavy metal, research has shown that listeners who are fans of this type of music experience a significant increase in positive effect after listening to it (e.g., Wooten, 1992; Recours et al., 2009). This phenomenon underscores the complexity of music's emotional influence, revealing that even seemingly aggressive or high-energy music can foster positive emotional experiences for dedicated listeners.

In our study, we utilize data from globally most-streamed songs, which reflects a large and diverse audience. Given that these songs are often popular because they resonate with the emotional and aesthetic preferences of listeners, we assume that they are selected in alignment with listeners preferred musical tastes. This selection bias towards favored music genres reinforces the idea that music, tailored to emotional and psychological preferences, acts as a mood regulator. Consequently, our analysis considers that the music data we use is likely to reflect listeners preferred emotional states, thus providing a relevant and dynamic proxy for studying the emotional influence of music on broader behavioral patterns, such as those in financial markets.

2.2. Mood dimensions

The second strand of literature focuses on the psychological dimensions of mood, which are often measured using two primary mood states: positive affect and negative affect. These two dimensions serve as a framework to understand how individuals experience and process emotions. Positive affect refers to a person's tendency to experience pleasant emotions and maintain an optimistic outlook. It encompasses feelings such as happiness, excitement, strength, inspiration, success, and determination. On the one hand, positive affect is not only a reflection of an individual's internal emotional state but also influences how they engage with others and face life's challenges in a constructive, solution-oriented manner. On the other hand, negative affect pertains to the inclination to experience unpleasant emotions and negativity in interactions or decision-making processes. It includes feelings such as fear, nervousness, shame, upset, depression, guilt, and anxiety. Importantly, these two dimensions—positive and negative affects—are largely independent of one another, meaning that experiencing high levels of one does not necessarily imply the absence of the other (Garland et al., 2010). For example, high negative affect signals the presence of negative emotions but does not imply the absence of positive ones, and vice versa. This independence allows individuals to simultaneously experience mixed emotional states, such as feeling both excited and anxious in complex situations.

Psychologists have shown that both positive and negative affects significantly influence human behavior, cognition, and decision-making (e.g., Loewenstein and Lerner, 2003; Nguyen et al., 2011). For instance, the "broaden and build" theory suggests that an elevated positive affect broadens individuals' thought-action repertoires, enabling them to see more opportunities and solutions. This broadened perspective allows people to build on their existing physical, psychological, and social resources, thus enhancing their resilience and problem-solving abilities (Garland et al., 2010). Positive affect also promotes creativity and adaptive responses to challenges, fostering personal and professional growth. Negative affect, while often associated with stress and reduced mental well-being, plays a crucial role in heightening alertness and caution. It can sharpen focus, encouraging individuals to be more detail-oriented and vigilant when navigating threats or difficult decisions (e.g., Knippenberg et al., 2010). However, excessive negative affect can lead to poor decision-making, impulsiveness, and disengagement from social and professional interactions (e.g., Ortega et al., 2012).

Music, as a mood regulator, has been shown to influence both positive and negative affects. It can be played not only to reflect a person's current emotional state but also to alter or enhance mood. For example, listening to uplifting music may elevate positive emotions, while melancholic tunes can help individuals process or express feelings of sadness or nostalgia. This ability of music to modulate mood does not diminish its role as a powerful determinant of human actions. Instead, it amplifies its relevance as music can both mirror emotions and actively shape decision-making and behavior. As a result, music can be strategically used to enhance mood in various settings, from personal well-being practices to influencing consumer behavior or investor sentiment in economic contexts (Sabouni, 2018).

2.3. *Effect of sentiment on financial markets*

Several studies have explored how financial markets respond to increased uncertainty by considering the role of investor sentiment. Investor sentiment reflects market participants' beliefs and emotions about asset price movements, particularly when they deviate from fundamental values. For example, in their seminal work, Baker and Wurgler (2006) find that low investor sentiment correlates with higher expected returns, especially for small-cap and volatile U.S. stocks. More recent contributions (Jiao et al., 2020; Chen et al., 2021) have further emphasized the impact of sentiment on financial markets.

Early research on investor sentiment relied on market data as proxies for sentiment, such as trading volume, closed-end fund discounts, dividend premiums, and IPO first-day returns (Barberis et al., 1998; Baker and Wurgler, 2006). However, another line of research has shifted towards sentiment measures derived from textual analysis. Tetlock (2007) highlighted the significant role that news media can play in driving financial market movements, while García (2013) and Manela and Moreira (2017) constructed text-based proxies for U.S. market sentiment and uncertainty, respectively. These studies underscore the growing recognition of the role of sentiment in financial markets, echoing the ideas of narrative economics proposed by Shiller (2017).

Later in the behavioral finance literature, researchers have employed various sentiment proxies beyond traditional financial metrics. Some have used data from online platforms such as social media and search engines to gauge online investor sentiment (e.g., Da et al., 2011). For example, online investment forums such as #WallStreetBets on the popular social media platform Reddit have become a source of data for textual sentiment analysis in financial markets (Long et al., 2022).Other researchers have explored mood-effecting events, such as weather (e.g., Chang et al., 2008; Hirshleifer and Shumway, 2003; Lanfear et al., 2019; Saunders, 1993), sports outcomes (e.g., Edmans et al., 2007; Kaplanski et al., 2013), and even aviation disasters (e.g., Kaplanski and Levy, 2010), to examine their effects on market behavior.

In the context of the cryptocurrency market, where traditional fundamentals are often unclear or absent, sentiment plays an even more prominent role. Given the active online presence of cryptocurrency investors, several studies have employed textual analysis to assess sentiment in this market. Lucey et al. (2022), for instance, constructed cryptocurrency uncertainty indices based on news articles from the LexisNexis Business Database. Urquhart (2018) further examined the relationship between cryptocurrencies and online searches. Liu and Tsyvinski (2021) developed a cryptocurrency sentiment index using Google Trends data and demonstrated that sentiment strongly predicts future cryptocurrency returns. Li et al. (2021) extended this research by comparing the impact of Google search intensity and Twitter activity on cryptocurrency markets, as well as a combined measure of both. They found a bidirectional relationship between these attention proxies, with Twitter activity having a shorter-term impact, while combining both metrics enhanced the observed causality.

Other studies used proxies constructed based on both observable market activity and online behavior. For instance, Bourghelle et al. (2022) applies linear and nonlinear VAR models to analyze the relationship between Bitcoin prices and investor sentiment, measured by the Fear and Greed Index. This index is constructed drawing from volatility, market momentum, social media activity, trends and surveys. The findings highlight the critical influence of collective emotions on the rise and fall of Bitcoin bubbles, with time-varying, asymmetric and bidirectional lead-lag effects between Bitcoin volatility and investor sentiment, revealing complex interactions that shift with time and market conditions.

Building on this literature, our paper investigates a novel angle by examining the relationship between music sentiment and cross-sectional cryptocurrency returns. This approach aims to explore how sentiment derived from music preferences and trends might influence cryptocurrency price movements, offering a fresh perspective on sentiment-driven market dynamics in the digital asset space. Specifically, our music-based sentiment measure reflects a more subconscious, emotion-based proxy for collective mood. This distinction with existing sentiment proxies is important because it suggests that music sentiment can provide additional, non-overlapping information that complements market-based sentiment indicators.

2.4. Research hypotheses

Previous studies suggest that non-fundamental factors such as mood, sentiment, and emotions can significantly impact investor decision-making, especially in markets where intrinsic value is difficult to assess (Shiller, 2017; Baker & Wurgler, 2007). This has led to a growing body of research investigating sentiment-driven price formation and exploring unconventional signals such as weather, social media, or music.

Recent contributions have examined how music sentiment, as a proxy for collective mood reflecting emotional states, can influence decision-making and risk perception. Kostopoulos and Meyer (2018) and Fernandez-Perez et al. (2020) link music sentiment to financial markets, while Edmans et al. (2022) show that sentiment derived from music preferences has a predictive power for stock returns. Our study extends this framework to the cryptocurrency market – an environment that is highly speculative and sentiment-sensitive. Unlike textual sentiment, music preferences reflect subconscious mood shifts in a culturally neutral manner, which can translate into investor optimism or pessimism affecting trading activity and asset prices. Given this context, we argue that music sentiment offers a psychologically grounded measure of sentiment that is particularly relevant for cryptocurrency market susceptible to behavioral forces.

Hence, based on this theoretical and empirical background, our study offers a novel setting to test the following hypotheses of behavioral implications of music sentiment on cryptocurrency pricing:

*H*1: *Music sentiment is priced in the cross-section of cryptocurrency returns.*

Building on sentiment-based asset pricing models, assets that are more sensitive to investor mood should exhibit different risk–return tradeoffs (Baker & Wurgler, 2006; Barberis et al., 1998). Music sentiment beta captures how a cryptocurrency reacts to collective mood. If music sentiment affects risk-taking and return expectations, then music sentiment beta should be priced in the cross-section of returns.

*H*2: *Music sentiment has a predictive power on short-term cryptocurrency returns.*

In mood-based theories of asset pricing, investors become more optimistic and risk-seeking in good moods and more pessimistic and risk-averse in bad moods (Loewenstein et al., 2001). These shifts can cause short-term mispricings, and assets more sensitive to these mood changes should experience short-term return effects, consistent with noise trader models (De Long et al., 1990).

*H*3: *Music sentiment remains predictive of cryptocurrency returns over longer horizons.*

Behavioral biases such as slow diffusion of sentiment (Barberis et al., 1998; Hong and Stein, 1999) suggest that mood-induced pricing effects may not be corrected immediately. Therefore, the influence of sentiment may persist over multiple trading periods.

*H*4: *The predictive power of the music sentiment beta remains significant after controlling for standard cryptocurrency-specific characteristics.*

We expect that music sentiment captures a distinct behavioral channel that is not fully explained by traditional factors such as market beta, size, past returns, or volatility. This hypothesis tests whether the sentiment beta adds incremental explanatory power in return predictability, in line with the broader literature on alternative sentiment measures (Baker et al., 2012; Da et al., 2015).

*H*5: *Music sentiment beta is partially explained by observable crypto-specific characteristics.*

Consistent with limits to arbitrage theory, volatile, and illiquid assets are more difficult to value and tend to exhibit stronger sentiment effects because rational arbitrage is more limited (Baker & Wurgler, 2006; Stambaugh et al., 2012). Therefore, sentiment beta may be systematically related to characteristics such as size, volatility, and liquidity.

3. Data and methodology

In our cryptocurrency study, we collected data from Coinmarketcap.com, a leading and widely used source of cryptocurrency price and volume information. This platform provides comprehensive daily data in USD for most cryptocurrencies, including open price, high price, low price, close price, volume, and market capitalization. The data was sourced from over 200 leading exchanges worldwide. Coinmarketcap.com calculates cryptocurrency prices using a volume-weighted average of the prices reported across markets. Volume is computed by multiplying price by the 24-hour volume (in units) reported directly from exchanges, while market capitalization is calculated by multiplying price by circulating supply. A cryptocurrency must meet specific criteria to be listed on Coinmarketcap.com. It must trade on public exchange with an API that reports the last 24-hour trading volume and the last traded price. Additionally, it must have a non-zero trading volume on at least one exchange to enable a volume-weighted average price computation.

Our initial dataset covers the period from May 2013 to September 2023, including both active and «dead» cryptocurrencies, to mitigate survivorship bias. This initial dataset comprises 7,790 cryptocurrencies. We implemented a rigorous cleaning process to prepare the data for analysis. First, we filtered the data using daily prices, eliminating subsequent daily price observations if 30 consecutive daily prices were identical until the next price change. We then remove repeating tails by deleting constant daily return observations from the tenth observation until the end of the sample period. Further refinement of the dataset involved excluding coins with market capitalization of less than $1,000,000 and removing observations with insufficient information or missing values necessary for variable construction. Following Liu et al. (2022), we winsorized all variables at the 1st and 99th percentiles to mitigate the effect of potential outliers. After this thorough cleaning process, our final dataset spans January 2017 to April 2023 and includes 2,551 cryptocurrencies.[1] We construct weekly returns using daily closing prices. The data cleaning guidelines were based on the work of Ince and Porter (2006) and Landis and Skouras (2021). While these guidelines were originally developed for stock data, we adapted them for cryptocurrency data to address the issues of staleness and padded observations, which are common across various types of financial data.

After cleaning the data, we calculated weekly returns for each cryptocurrency using its daily closing prices. Each year was divided into 52 weeks. Typically, the first 51 weeks consisted of seven days, while the 52nd week included the remaining days of the year, which was usually eight days. In leap years, the 52nd week included nine days.

3.1. Music sentiment index

We follow Edmans et al. (2022) in constructing a stream-weighted average valence (henceforth *MSI*) across the top-200 songs globally for each week *w,* as follows:

$$MSI_w = \sum_{i=1}^{200}\left(\frac{Streams_{i,w}}{\sum_{i=1}^{200} Streams_{i,w}}.Valence_{i,w}\right) \tag{1}$$

where $Streams_{i,w}$ is the global total streams for song i on week w, and $Valence_{i,w}$ is the valence metric of the song i on week w.

Valence measures the emotional positivity of the music itself, rather than the lyrics, thus sidestepping the issues associated with textual analysis. The valence scale ranges from 0 to 1, with higher valence indicating more positive-sounding songs (e.g., happy, cheerful, euphoric) and lower valence indicating more negative-sounding songs (e.g., sad, melancholic, depressed).[2]

We then estimate the weekly music sentiment beta for each cryptocurrency. We run monthly rolling regressions of excess cryptocurrency returns (R) on the music sentiment index over a 60-week fixed window while controlling for the factors- market (MKT), size (SMB), and momentum (WML).

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MSI}.MSI_t + \beta_{i,t}^{MKT}.MKT_t + \beta_{i,t}^{SMB}.SMB_t + \beta_{i,t}^{WML}.WML_t + \varepsilon_{i,t} \tag{2}$$

These factors are from the cryptocurrency three-factor model proposed by Liu et al. (2022). To construct the market factor (MKT), first we have to construct market index returns, we faced the challenge of a lack of a widely accepted cryptocurrency market index. Following the methodology of Liu and Tsyvinski (2021), we calculate the market index return as the value-weighted average of the returns of all cryptocurrencies included in our sample. The excess market return is then determined by subtracting the risk-free rate from the market index return. We used the one-month U.S. Treasury bill rate as a risk-free rate. We followed the approach outlined by Fama and French (1992, 1993, 2015) for size (SMB) and momentum (WML) factors. For SMB, we divided cryptocurrencies into two groups based on their weekly market capitalization: small size (S) and big size (B). We then form value-weighted portfolios for each group and calculate the SMB as the difference between the weekly average returns of the small and large portfolios. For WML, we use a two-week momentum return to categorize cryptocurrencies into three groups: loser (L), neutral (N), and winner (W). We then formed six size-momentum portfolios (S/L, S/N, S/W, B/L, B/N, and B/W) by intersecting the size and momentum groups. Finally, we value-weighted these portfolios to compute the weekly sorted portfolio returns and calculated the WML as the difference between the average returns of the winner and loser portfolios.

To examine other characteristics that may influence the cross-sectional expected returns of cryptocurrencies, we calculate the crypto-specific characteristics: MCAP is the log of market capitalization on the last day of the portfolio formation week (Banz, 1981). MOMr2 is the past two-week return (Jegadeesh and Titman, 1993). BETA is calculated using a standard market model (Fama and MacBeth, 1973). IDIOVOL is the standard deviation of the residuals from the market model regression (Ang et al., 2006). RETVOL is the standard deviation of daily returns during the portfolio formation week (Ang et al., 2006). MAXRET is the maximum daily return in the portfolio formation week (Bali et al., 2011). DAMIHUD is the average absolute daily return divided by the dollar trading volume of the portfolio formation week (Amihud, 2002).

4. Empirical results

In this section, we conduct parametric and non-parametric tests to assess the predictive power of the music sentiment beta on the future returns of cryptocurrencies. We first tested this predictive power using univariate portfolio-level analysis. Second, we discuss the average characteristics of cryptocurrencies to understand the composition of music sentiment beta portfolios. Third, we present univariate and multivariate cross-sectional regression results. Finally, we provide evidence derived from robustness checks.

[1] We restrict our dataset to this time frame, as our data is retrieved via the Spotify API, which provides information only from 2017 onwards.

[2] Please note that, as a robustness check, we also utilized the music mood measure from Hadhri (2023), which is based on the valence, energy, and danceability metrics of songs.

4.1. Univariate portfolio-level analysis

To measure the sensitivity of individual cryptocurrency to music sentiment, we conducted weekly rolling regressions of excess cryptocurrency returns against a one-week-ahead music sentiment index, using a 60-week fixed-window estimation. The initial set of sentiment betas (β^{MSI}) is computed using data from January 2017 to February 2018. The sentiment betas computed on a weekly basis were used to forecast cross-sectional cryptocurrency returns in the subsequent week. The rolling regression approach is performed up until the last available data point in April 2023. The results of the cross-sectional return predictability were reported from March 2018 to April 2023.

Starting with univariate portfolio analysis, we tested the significance of the cross-sectional relationship between music sentiment and cryptocurrency future returns. To conduct this, we sorted cryptocurrencies based on their β^{MSI} values and formed decile portfolios. The Decile 1 portfolio (low) consists of cryptocurrencies with the lowest β^{MSI}, whereas the Decile 10 portfolio (high) consists of cryptocurrencies with the highest β^{MSI}. We then calculated the value-weighted one-week-ahead excess returns for each portfolio.

Table 1 presents the descriptive statistics of the univariate portfolios. Column 2 reveals a clear cross-sectional variation in the average values of β^{MSI}. The average music sentiment beta increases monotonically from −2.768 in decile 1 to 2.678 in decile 10.[3] This pattern suggests that cryptocurrencies with higher music sentiment betas (decile 10) demonstrate higher sensitivity to shifts in collective investor mood. In behavioral finance, such assets that are sensitive to sentiment shifts are commonly considered as sentiment-prone or speculative as they may undergo larger price swings in response to emotional market dynamics (Mahmoudi et al. 2022). These assets often attract investors seeking high returns, but they also tend to be more volatile due to their reliance on the dimensional component of investor sentiment rather than fundamental economic factors (Kostopoulos et al. 2020). Nevertheless, the lower-sensitivity cryptocurrencies in Decile 1 suggests that they are weakly affected by sentiment shifts, attracting risk-averse investors who seek stable returns.

Column 3 presents the excess VW returns of the decile portfolios. Interestingly, the average excess returns exhibit an inverse relationship with sentiment sensitivity. Specifically, higher-β^{MSI} cryptocurrencies (decile 10) tend to underperform lower-β^{MSI} cryptocurrencies (decile 1). The next-week average excess return decreases from 0.004 to 0.002 per week when moving from the lowest β^{MSI} decile to the highest β^{MSI} decile. This result implies that the additional risk associated with increased sensitivity to sentiment is not adequately compensated by higher returns. In other words, cryptocurrencies with high music sentiment betas often exhibit higher volatility, as they are very sensitive to shifts in market sentiment mainly influenced by exogenous emotional cues. Investors taking on the additional risk associated with high sentiment exposure are not receiving proportionate risk premiums. Nevertheless, this mismatch suggests that if the return of cryptocurrencies do not sufficiently compensate for the increased risk, investors might experience a risk return imbalance, resulting in reduced financial attractiveness of high-beta cryptocurrencies, especially to investors who are cautious about risk. These findings could be explained by the mood-driven mispricing dynamics. As high-β^{MSI} cryptocurrencies are more exposed to emotionally-driven investor behavior, they may experience excessive optimism during positive mood periods, followed by sharp corrections when sentiment shifts. Conversely, low-β^{MSI} cryptocurrencies are less influenced by these mood swings thus, attracting more risk-averse investors seeking stability.

The finding that the High-minus-Low portfolio (H-L) produces a negative but statistically insignificant weekly return of −0.003, further supports this interpretation. This portfolio-level finding is consistent with the portfolio-level findings of Baker and Wurgler (2006) who found that when sentiment (investor sentiment) is high, subsequent returns tend to be lower for assets (stocks) more sensitive to sentiment. This suggests that investors do not receive sufficient compensation for bearing sentiment-induced volatility, potentially making high-β^{MSI} cryptocurrencies less attractive from a risk-return perspective. Another interesting finding reported in this study suggests the lack of a consistent and monotonic pattern between β^{MSI} and average weekly returns, as a shift in one does not correspond predictably to shifts in the other. This reinforces the findings that sentiment-driven volatility introduces pricing noise, disrupting the predictable risk-return relationship.

In the last Column, we adjusted the portfolio excess returns using a three-factor model to identify whether known cryptocurrency risk factors could explain the return variation across β^{MSI} portfolios. Most portfolios exhibit positive risk-adjusted alphas, suggesting that cryptocurrencies, on average, generate returns beyond those explained by standard cryptocurrency risk factors. However, statistical significance is reported only in the 8th and 9th decile portfolios, containing cryptocurrencies with high β^{MSI}. This implies that cryptocurrencies highly sensitive to collective mood, as proxied by music sentiment, experience stronger investor demand during periods of elevated positive sentiment, which results in temporary mispricing and significantly abnormal returns (Shleifer, 2000; Baker and Wurgler, 2006). This suggests that while most portfolios exhibit positive risk-adjusted alphas, the sensitivity of cryptocurrencies to sentiment could provide effective investment opportunities especially in volatile and speculative environments like cryptocurrency markets (Makarov and Schoar, 2020). We also observe that the mean returns of all portfolios are improved, and the t-stat is higher than that of the excess return portfolios (in Column 3). However, the effect seems to be nonlinear since the highest-β^{MSI} portfolio (decile 10) do not exhibit significant alphas as for deciles 8 and 9. This result may suggest that there may be a “sweet spot” where cryptocurrencies are sensitive enough to music sentiment to benefit from increased demand, passing this threshold, they become excessively volatile and unattractive to risk-averse investors. Interestingly, the highest-β^{MSI} portfolio now generates a higher return than the lowest-β^{MSI},

[3] Music sentiment beta captures the sensitivity of a cryptocurrency to the change in music sentiment. A positive beta means that the cryptocurrency’s returns increase with an increase in music sentiment and negative beta means cryptocurrency’s returns decrease with an increase in music sentiment.

Table 1
Univariate portfolios of cryptocurrencies sorted by music sentiment beta.

	β^{MSI}	VW excess returns	Alphas
Low	−2.768	0.004	0.011
		(0.494)	*(1.347)*
2	−0.487	0.006	0.012
		(0.767)	*(1.535)*
3	−0.295	0.000	0.004
		(−0.016)	*(0.411)*
4	−0.238	0.159	0.124
		(1.137)	*(0.899)*
5	−0.055	0.005	0.000
		(0.297)	*(0.011)*
6	0.056	−0.002	−0.002
		(−0.277)	*(−0.336)*
7	0.237	−0.008	−0.006
		(−1.163)	*(−1.053)*
8	0.404	0.037	0.038
		(1.884)	*(1.993)*
9	0.612	0.011	0.015
		(1.484)	*(1.920)*
High	2.678	0.002	0.012
		(0.190)	*(1.342)*
H-L		−0.003	0.001
		(−0.352)	*(0.100)*

This table presents the excess returns and alphas (adjusted with the three-factor model) of cryptocurrency deciles sorted by music sentiment beta (β^{MSI}) and formed weekly, from March 2018 to April 2023. The decile 1 portfolio (low) consists of cryptocurrencies with the lowest β^{MSI}, whereas the decile 10 portfolio (high) consists of cryptocurrencies with the highest β^{MSI}. All value-weighted excess returns and alphas are one week ahead of the portfolio-formation period. The final row shows the differences in weekly excess returns and alphas between deciles ten and one. Newey-West (1987) adjusted t-statistics are presented in parentheses.

producing an H-L weekly return of 0.001. This implies that cryptocurrencies can generate positive returns by considering the MKT, SMB, and WML factors (Benedetti and Kostovetsky, 2021). However, the returns are insignificant, suggesting that cryptocurrencies in both deciles 1 and 10 are more prone to emotional overreaction, and as a result their returns are less predictable. Similar to the observation in Column 3, no pattern of return-music sentiment beta movement was observed, meaning that market sentiment interacts with cryptocurrency pricing in a nonlinear way.

In short, there is no clear pattern of risk-return tradeoff, as returns of cryptocurrencies in both portfolios 1 and 10 are less-rewarding on a risk-adjusted basis (Azqueta et al., 2023). In other words, neither portfolio provides sufficient compensation for the higher risk taken, as both show relatively low excess and risk-adjusted returns with no significant difference between them.

The highest excess return (0.159 per week) and alpha (0.124 per week) are observed in decile 4, which corresponds to a moderately negative sentiment beta of −0.238. This middle-range portfolio includes cryptocurrencies that seem to respond to sentiment shifts

Table 2
Persistence of music sentiment beta.

t-month ahead β^{MSI}	Univariate Predictive Regressions	Controlling for Lagged Variables
t = 1	0.00001	−0.064
	(1.733)	*(−4.217)*
t = 2	−0.012	0.031
	(−2.966)	*(3.021)*
t = 3	−0.005	−0.004
	(−2.684)	*(−0.337)*
t = 4	−0.00001	−0.133
	(−3.431)	*(−7.068)*
t = 5	−0.009	0.059
	(−1.880)	*(7.010)*

To examine the persistence of music sentiment beta (β^{MSI}), we conducted crypto-level cross-sectional regressions of β^{MSI} on its own lagged values and lagged cross-sectional predictors from March 2018 to April 2023. The first column reports the average slope coefficients from univariate Fama-MacBeth regressions of one-month to five-month-ahead β^{MSI} on lagged β^{MSI}. The last column presents the average slope coefficients from multivariate Fama-MacBeth regressions that control for additional lagged variables: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD). Newey-West (1987) adjusted t-statistics are presented in parentheses.

without overreacting, offering a more stable trade-off between risk and return. This suggests that investors tend to prefer cryptocurrencies with moderate emotional sensitivity, and are more willing to focus on cryptocurrencies that demonstrate a moderate reaction to sentiment shifts, leading to a steadier demand dynamics and better risk-adjusted returns (Cai and Zhao, 2024). Our findings confirm *H*1 and underscore the value of using sentiment metrics not only for predicting returns, but also for constructing portfolios that optimize trade-off between behavioral risk and sentiment-driven opportunities. In our analysis, we find that portfolio 4 offers the optimal tradeoff between sentiment-related risk and returns, while the statistically significant risk-adjusted returns are observed for portfolios 8 and 9.

In order to assess whether investor expectations about β^{MSI} are valid, it is crucial to investigate its persistence of cryptocurrency sensitivity to sentiment over time. Investors often rely on historical characteristics when making allocation decisions, assuming that assets exhibiting a strong sentiment responsiveness in the past will behave similarly in the future. This holds for the idea that β^{MSI} has a stable and predictable trait. To explore this, we run crypto-level cross-sectional regressions of β^{MSI} on lagged β^{MSI} and lagged cross-sectional predictors. Specifically, for each week, we run a regression across cryptocurrencies of 4-week-ahead β^{MSI} on lagged β^{MSI} and seven lagged control variables: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD).

Table 2 shows that there is a tendency for β^{MSI} to reverse over time, and this reversal is significant, as all the coefficients on lagged β^{MSI} are significant at the 1 % and 10 % levels. Moreover, the high past value of β^{MSI} tends to persist for one month, as indicated by the positive and statistically significant coefficient of the lagged β^{MSI} at t_1 at the 10 % level. This suggests that investors might reasonably expect sentiment sensitivity to carry forward in the near term (1-month ahead). However, coefficients for longer horizons become negative. This indicates that β^{MSI} tends to revert toward the mean or lower values over time, revealing a lack of long-term consistency. It is important to notice the absence of clear pattern of persistence, as the relationship between past and future β^{MSI} appears inconsistent. When we control for lagged cross-sectional characteristics, the significance, magnitude, and direction of the coefficients change, indicating that other crypto-specific risk factors such as market capitalization, liquidity and volatility could influence the persistence and temporal dynamics of music sentiment, rather than being a time-invariant feature. Notably, even after controlling for these variables, the reversal pattern is still evident, reinforcing the notion that β^{MSI} is highly dynamic and unstable over time. This empirical evidence indicates that the β^{MSI} does not exhibit a consistent pattern over time, suggesting that music sentiment is highly volatile and does not maintain a steady trend over longer periods. This finding is rooted in the behavioral nature of sentiment itself. As music sentiment is volatile, emotional and influenced by exogenous shocks, cryptocurrencies' sensitivity to such sentiment is likely to fluctuate as investor attention shifts or new market conditions arise.

In sum, relying on historical β^{MSI} for making investment decisions and as a forecasting tool for future sentiment sensitivity is irrational, especially over longer horizons. While β^{MSI} show short-term persistence confirming our *H*2, long-term consistency is lacking, and sensitivity to broader market variables implies that investors should treat it as a behaviorally driven signal rather than a permanent asset-specific characteristic.

Table 3
Average cryptocurrencies characteristics.

Variable	1	2	3	4	5	6	7	8
Intercept	−0.003	−0.076	0.009	0.145	0.206	0.086	0.019	0.930
	(−0.127)	*(−0.034*	*(0.166)*	*(1.036)*	*(1.286)*	*(0.719)*	*(0.185)*	*(1.253)*
BETA	0.279							0.668
	(0.649)							*(1.034)*
MCAP		0.005						−0.041
		(0.001)						*(−0.978)*
MOMr2			−0.181					−0.117
			(−2.431)					*(−1.452)*
RETVOL				−1.516				−5.195
				(−1.336)				*(−0.938)*
IDIOVOL					−1.788			−2.537
					(−1.477)			*(−1.039)*
MAXRET						−0.416		2.002
						(−0.941)		*(0.806)*
DAMIHUD							−1.367	−1.072
							(−0.396)	*(−0.516)*

This table presents the time-series averages of the slope coefficients obtained from regressions of music sentiment beta (β^{MSI}) on various crypto-level characteristics and risk factors from March 2018 to April 2023.Weekly cross-sectional regressions were conducted using the following econometric specification and its nested versions:

$$\beta_{i,t}^{MSI} = .\lambda_{0,t} + \lambda_{1,t}X_{i,t} + \varepsilon_{i,t}$$

where $\beta_{i,t}^{MSI}$ is the music sentiment beta of crypto i in month t, $\lambda_{0,t}$ and $\lambda_{1,t}$ are time-varying coefficients, $X_{i,t}$ is a vector of crypto-specific variables observable at time t for cryptocurrency i, and $\varepsilon_{i,t}$ is the error term.The crypto-specific variables included in $X_{i,t}$ are: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD). Newey-West (1987) adjusted t-statistics are presented in parentheses.

4.2. Average cryptocurrency characteristics

In this section, we examine the average characteristics of cryptocurrencies with low versus high β^{MSI}, based on Fama and MacBeth's (1973) cross-sectional regressions. The time-series averages of the slope coefficients from the regressions of the music sentiment beta on crypto-level characteristics are presented in Table 3. Each week, cross-sectional regressions were run for the following econometric specifications:

$$\beta_{i,t}^{MSI} = \lambda_{0,t} + \lambda_{1,t} X_{i,t} + \varepsilon_{i,t} \tag{3}$$

Where $\beta_{i,t}^{MSI}$ is the music sentiment beta of cryptocurrency i in week t and $X_{i,t}$ is a collection of crypto-specific variables observable at time t for cryptocurrency i (market beta, market capitalization, past two-week return, return volatility, idiosyncratic volatility, maximum daily return, and illiquidity). Cross-sectional regressions were performed at a weekly frequency from March 2018 to April 2023.

Results show that cryptocurrencies with higher β^{MSI} tend to be more exposed to overall market movements. Columns 1 and 2 of Table 3 report a positive relationship between β^{MSI} and market beta and market capitalization, respectively as the average slope coefficients of BETA and MCAP are positive but insignificant. This suggests that cryptocurrencies with a higher β^{MSI} tend to have a higher sensitivity to market dynamics and are leading the market in capitalization and trading volume. In line with Kogan et al. (2024), such assets are often attractive to investors and are more integrated into broader market narratives, making them more sensitive to mood fluctuations. Column 3 shows that MOMr2 is negatively and significantly associated with β^{MSI}, indicating that cryptocurrencies with high past two-week returns tend to have a lower β^{MSI}. Such empirical evidence reveals that cryptocurrencies with stronger recent performances exhibit lower sentiment sensitivity. This suggests that, when momentum is strong, investors may anchor their expectations more on observable trends and underlying fundamentals (e.g., demand, momentum) and less on mood and emotional cues (Bianchi et al., 2022).

Columns 4, 5, 6, and 7 show that all volatility characteristics tend to have an insignificant negative effect on music sentiment, with average slope coefficients of RETVOL, IDIOVOL, MAXRET, and DAMIHUD ranging from −1.477 to −0.396. This evidence suggests that more volatile, riskier, and less liquid cryptocurrencies may paradoxically have lower sensitivity to music sentiment. One possible explanation is that extremely volatile cryptocurrencies may already incorporate high levels of noise making them less systematically tied to shifts in collective mood. Finally, we notice that, when all control variables are added simultaneously, both the magnitude and direction of relationships change, highlighting that β^{MSI} is not determined in isolation but is influenced by a complex interaction of factors. Hence, our *H*5 is confirmed.

A notable difference observed between the univariate and multivariate analyses is that the association between β^{MSI} and market capitalization, along with MAXRET, was reversed in the multivariate analysis when compared to the univariate results. Consequently,

Table 4
Fama-MacBeth cross-sectional regressions.

Variable	1	2	3	4	5	6	7	8
Intercept	0.022	0.022	0.018	0.014	0.012	0.007	0.009	0.010
	(5.544)	*(5.561)*	*(4.611)*	*(3.511)*	*(3.080)*	*(1.918)*	*(2.092)*	*(2.372)*
β^{MSI}	−0.001	−0.004	0.005	0.009	0.015	0.009	0.016	0.015
	(−4.939)	*(−1.159)*	*(4.008)*	*(2.447)*	*(5.456)*	*(5.262)*	*(5.509)*	*(6.179)*
BETA		0.000	−0.001	−0.004	−0.004	−0.003	−0.003	−0.002
		(−0.941)	*(−0.855)*	*(−2.057)*	*(−2.613)*	*(−1.990)*	*(−1.802)*	*(−2.300)*
MCAP			0.031	0.074	0.097	0.080	0.088	0.082
			(3.251)	*(5.523)*	*(5.527)*	*(5.969)*	*(6.023)*	*(6.007)*
MOMr2				0.004	0.022	0.003	0.034	0.024
				(0.812)	*(2.573)*	*(0.816)*	*(2.990)*	*(3.160)*
RETVOL					0.003	0.004	0.006	0.004
					(1.759)	*(2.108)*	*(2.300)*	*(2.834)*
IDIOVOL						0.000	0.000	0.000
						(−1.711)	*(−3.670)*	*(−5.949)*
MAXRET							0.006	0.004
							(1.214)	*(2.743)*
DAMIHUD								0.000
								(3.575)
Adj R^2	0.03 %	0.03 %	0.19 %	0.51 %	0.63 %	0.66 %	0.90 %	1.25 %

This table presents the results of the Fama-Macbeth regression. The cross-sectional regression was run using crypto-level one-week-ahead returns on music sentiment beta ($\beta_{i,t}^{MSI}$) and other crypto-specific characteristics (added one at a time as a control variable) from March 2018 to April 2023. The crypto-specific variables included in $X_{i,t}$ are: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD). This table reports the time-series averages of coefficients and adjusted R^2 from weekly regressions, and the corresponding Newey-West (1987) adjusted t-statistics are presented in parentheses.

cryptocurrencies that demonstrate greater sensitivity to music sentiment show higher market beta, lower momentum, less volatility, and potentially greater liquidity. Nevertheless, it is important to emphasize that only the relationship with momentum is statistically significant, while the others are not, highlighting the limited explanatory power of these structural characteristics on sentiment sensitivity when considered jointly. The results suggest that music sentiment beta may reflect an idiosyncratic behavioral component, only partially linked to observable fundamentals, reinforcing its role as a behavioral signal rather than a purely structural characteristic.

4.3. Crypto level cross-sectional regression

In response to the limitations of portfolio-level analysis highlighted by Bali et al. (2011), Bali et al. (2017), and Zhang et al. (2021), we examine the relationship between music sentiment beta β^{MSI} and cryptocurrency returns at the individual asset level using Fama and MacBeth (1973) regressions.

For the crypto-level cross-sectional regressions, we regressed each cryptocurrency's one-week-ahead excess return on the β^{MSI} and other cryptocurrency characteristics one at a time. This allowed us to isolate the unique contribution of β^{MSI} in explaining future returns while incrementally controlling for standard crypto-specific characteristics. We, then, calculated the time-series averages of the slope coefficients obtained from these cross-sectional regressions. Weekly cross-sectional regressions are run for the following econometric specification:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}.\beta^{MSI}_{i,t} + \lambda_{2,t}.X_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $R_{i,t+1}$ is the realized excess return on cryptocurrency i in week $t+1$, $\beta^{MSI}_{i,t}$ is the music sentiment beta of cryptocurrency i in week t, and $X_{i,t}$ is a collection of crypto-specific control variables observable at time t for cryptocurrency i (market beta, market capitalization, past two-week returns, return volatility, idiosyncratic volatility, maximum daily returns, and illiquidity). Cross-sectional regressions were performed at a weekly frequency from March 2018 to April 2023. Table 4 reports the results.

In the univariate regression (Column 1), the coefficient for $\beta^{MSI}_{i,t}$ is negatively and significantly related to one-week ahead excess returns, with a value of -0.001 (t-stat = -4.939). This empirical finding suggests that, in isolation, higher sentiment sensitivity is associated with lower future returns. Such an evidence is consistent with Edmans et al. (2022) who reported a negative association between music sentiment and next-week stock returns, and aligns with behavioral theories indicating that overly sentiment-sensitive assets may become temporarily overpriced, leading to subsequent underperformance as mood shifts reverse. Table 1 shows a similar effect for $\beta^{MSI}_{i,t}$ on portfolio returns. From columns 2–8, we add other characteristics (one at a time) to the univariate regression model. We observe that the relationship between $\beta^{MSI}_{i,t}$ and future returns becomes positive and statistically significant, except for the regression including market beta (Column 2). Thus, once size, momentum, volatility, and liquidity are accounted for, the true pricing effect of sentiment sensitivity emerges and cryptocurrencies that are responsive to music sentiment tend to yield higher subsequent returns. This result confirms our *H*4 and aligns with sentiment-based asset pricing theories which suggests that investor mood influences expectations and price pressure particularly in speculative markets like cryptocurrency markets (Baker and Wurgler, 2006). The magnitude of t-stat increased with the addition of other characteristics suggesting that $\beta^{MSI}_{i,t}$ is a strong predictor of the cross-sectional one-week-ahead cryptocurrency return. This shift in the sign of slope coefficients implies that music sentiment contains meaningful and incremental information about return predictability that is distinct from traditional risk factors. In other words, while market dynamics and technical features play a crucial role in driving cryptocurrency returns (Akyildirim et al., 2020), $\beta^{MSI}_{i,t}$ acts as a behavioral signal not fully explained by fundamentals.

Column 2 controls the market beta; the average slope of $\beta^{MSI}_{i,t}$ remains negative and statistically insignificant, and the average slope of market beta is also insignificant. Such finding reveals that market beta weakens the predictive power of $\beta^{MSI}_{i,t}$. Column 3 includes an additional variable, size. In this specification, the average slope of $\beta^{MSI}_{i,t}$ becomes positive and statistically significant, indicating that after controlling for size, a higher $\beta^{MSI}_{i,t}$ is associated with higher subsequent returns. Column 4 includes 2-week momentum in the model, and the average slope of $\beta^{MSI}_{i,t}$ increases and remains significantly positive. When moving to Column 5, results reveal that adding the volatility factor RETVOL to the econometric specification increases the average slope on $\beta^{MSI}_{i,t}$ from 0.009 to 0.015. This suggests that $\beta^{MSI}_{i,t}$ provides additional explanatory power for future returns beyond that captured by technical features. The relationship between $\beta^{MSI}_{i,t}$ and returns strengthens when volatility is accounted for, indicating that $\beta^{MSI}_{i,t}$ acts as a distinct factor in predicting cryptocurrency returns. Column 6 shows that when adding IDIOVOL in the econometric specification, the average slope on $\beta^{MSI}_{i,t}$ decreases from 0.015 to 0.009 while still maintaining statistical significance. This evidence indicates that $\beta^{MSI}_{i,t}$ captures factors beyond idiosyncratic risk. Column 7 shows that by adding MAXRET to the model, the average slope on $\beta^{MSI}_{i,t}$ increases from 0.0.009 to 0.0.016, suggesting that the $\beta^{MSI}_{i,t}$ captures return predictability beyond extreme positive returns. The last column (Column 8) shows a full model with the addition of DAMIHUD. The relationship between $\beta^{MSI}_{i,t}$ and the future returns of cryptocurrencies remains strong and significantly positive, indicating its robustness when controlling for illiquidity. In nutshell, the positive coefficients of $\beta^{MSI}_{i,t}$ reported in multivariate models suggest that music sentiment serves as a positive predictor of cryptocurrency returns, which aligns with the behavioral finance theory suggesting that investor sentiment can drive asset prices. When controlling for size, momentum and volatility, β^{MSI} effect strengthens indicating that sentiment interacts with these characteristics to shape return dynamics.

Results on the relationship between common cryptocurrency characteristics and future excess returns are also interesting and align with theory. First, the negative association of market beta with future returns is consistent with the low-beta anomaly phenomenon of Frazzini and Pedersen (2014) who documented that low-beta assets consistently outperform high-beta assets. Second, the positive and significant association of Market Capitalization with future returns indicates that larger cryptocurrencies outperform smaller cryptocurrencies (Bianchi et al., 2022). This finding also challenges the traditional size effect and aligns with van Van Dijk (2011) who suggests that the size premium had weakened or disappeared. Third, MOMr2 shows a positive relationship with future cryptocurrency returns, supporting the momentum effect of Jegadeesh and Titman (1993) which suggests that past winners continue to outperform. Fourth, RETVOL has a positive relationship with future returns, consistent with the risk-return tradeoff theory (Andreou et al. 2021). Fifth, IDIOVOL shows a negative relationship with future cryptocurrency returns, echoing the idiosyncratic volatility puzzle (Ang et al., 2009) where high idiosyncratic risk correlates with lower expected returns, and contradicting theoretical predictions (Fang and Zhang, 2023).

Furthermore, MAXRET has a positive relationship with future cryptocurrency returns. These positive coefficients suggest that cryptocurrencies with extremely positive returns will continue to perform well in the short-term. Such evidence is in line with the attention-grabbing hypothesis advanced by Barber and Odean (2008). Cryptocurrencies with extremely positive returns often capture investor interest, potentially leading to increased demand and further price escalation (Zhang et al. 2021). Nevertheless, Barber and Odean (2008) also considered the potential for price reversals when attention fades. Finally, we notice that DAMIHUD has a positive relationship with future cryptocurrency return (Brauneis et al. 2021). The positive coefficient aligns with Amihud's (2002) illiquidity premium theory, suggesting that less liquid cryptocurrencies offer higher returns. Specifically, cryptocurrencies with lower liquidity often provide higher returns with the aim of compensating for the increased risk associated to holding assets that may be difficult to buy or sell swiftly. The illiquidity premium accounts for the challenges associated to selling assets without affecting market prices, resulting in increasing returns as a compensation for taking on this risk. In sum, the β^{MSI} emerges as a significant predictor of future cryptocurrency returns, especially when controlling for other characteristics. These findings reinforce the behavioral evidence that emotions and mood, rather than purely fundamentals, play a crucial role in short-term return dynamics.

We further tested whether the influence of music sentiment beta β^{MSI} holds beyond the short term. We assess its predictive power at the crypto-level across different return horizons from 2 to 12 weeks ahead. The multivariate regressions, in Table 5, show a time-varying relationship between music sentiment sensitivity and future cryptocurrency returns.

In the short-run (2 – 5 weeks), the relationship between β^{MSI} and cryptocurrency future returns remains negative which aligns with earlier findings at the portfolio level (Table 1) and the univariate regression (Table 4, Column 1) suggesting that cryptocurrencies highly sensitive to mood may experience short-term overreaction leading to temporary mispricing (Barberis et al., 1998; Loewenstein et al., 2001) due to emotional trading particularly in a speculative market like cryptocurrencies. However, at longer time horizons, the relationship shifts to positive, indicating that sentiment-sensitive cryptocurrencies tend to generate higher returns in the long run,

Table 5
Long-term predictive power of music sentiment beta.

	Intercept	β^{MSI}	BETA	MCAP	MOMr2	RETVOL	IDIOVOL	MAXRET	DAMIHUD	Adj R2
t + 2	0.021	−0.006	−0.002	−0.002	−0.006	0.002	0.000	0.000	0.000	0.49 %
	(5.393)	*(−2.783)*	*(−3.294)*	*(−0.354)*	*(−3.053)*	*(2.298)*	*(−3.981)*	*(0.010)*	*(−1.662)*	
t + 3	0.021	−0.001	−0.001	−0.004	0.001	−0.001	0.000	−0.003	0.000	0.20 %
	(5.374)	*(−1.719)*	*(−2.178)*	*(−0.746)*	*(0.280)*	*(−0.528)*	*(0.094)*	*(−1.041)*	*(−0.524)*	
t + 4	0.003	0.000	0.000	0.012	−0.002	0.001	0.000	0.000	0.000	0.72 %
	(5.657)	*(0.338)*	*(−0.140)*	*(2.573)*	*(−0.447)*	*(0.734)*	*(−1.185)*	*(0.045)*	*(−0.492)*	
t + 5	0.022	0.000	0.002	0.009	−0.004	−0.002	0.000	−0.012	0.000	0.53 %
	(5.350)	*(−0.237)*	*(2.247)*	*(1.712)*	*(−1.133)*	*(−0.877)*	*(1.530)*	*(−2.154)*	*(0.950)*	
t + 6	0.023	**0.**001	0.001	0.010	0.000	0.003	0.000	0.006	0.000	0.87 %
	(5.724)	*(0.991)*	*(1.057)*	*(1.539)*	*(−0.044)*	*(1.870)*	*(−0.701)*	*(1.174)*	*(2.416)*	
t + 7	0.022	0.002	0.001	0.020	0.019	0.005	0.000	0.004	0.000	0.92 %
	(5.394)	*(1.180)*	*(2.125)*	*(3.847)*	*(2.218)*	*(2.762)*	*(−1.522)*	*(0.880)*	*(2.780)*	
t + 8	0.023	0.001	0.001	0.003	0.015	0.000	0.000	0.002	0.000	0.40 %
	(5.776)	*(0.508)*	*(1.675)*	*(0.829)*	*(1.392)*	*(−0.047)*	*(1.147)*	*(0.322)*	*(0.430)*	
t + 9	0.020	0.004	0.001	−0.001	−0.007	−0.002	0.000	−0.013	0.000	0.64 %
	(5.158)	*(1.886)*	*(1.117)*	*(−0.128)*	*(−2.753)*	*(−0.825)*	*(−0.270)*	*(−2.069)*	*(2.176)*	
t + 10	0.003	0.001	0.001	−0.007	0.001	−0.004	0.000	−0.005	0.000	0.91 %
	(5.688)	*(1.092)*	*(3.007)*	*(−1.266)*	*(0.064)*	*(−1.801)*	*(3.640)*	*(−0.982)*	*(−0.637)*	
t + 11	0.023	0.001	0.001	−0.003	−0.002	−0.003	0.000	−0.005	0.000	0.34 %
	(5.728)	*(0.719)*	*(0.846)*	*(−0.743)*	*(−0.320)*	*(−2.363)*	*(1.608)*	*(−1.534)*	*(−1.569)*	
t + 12	0.022	0.005	0.002	0.006	0.012	−0.001	0.000	−0.001	0.000	0.44 %
	(5.596)	*(3.002)*	*(3.203)*	*(1.754)*	*(2.501)*	*(−0.542)*	*(2.165)*	*(−0.120)*	*(1.515)*	

This table presents the results from regressing weekly excess returns, from two to twelve weeks ahead, against music sentiment beta (β^{MSI}) after controlling for all other control variables. The other control variables are: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD). Newey-West (1987) adjusted t-statistics are presented in parentheses. The sample period is from March 2018 to April 2023.

confirming our *H*3. This aligns with slow sentiment diffusion hypothesis where sentiment effects are not immediately incorporated into prices (Hong and Stein, 1999). The relationship is only significant when predicting 2-, 3-, 9-, and 12-week-ahead returns, which is consistent with investor attention cycles theory (Barber and Odean, 2008) that suggests delayed performance effects.

Examination at both the portfolio and crypto-level analyses reveals a discrepancy between the findings. Specifically, at the portfolio level, the highest-β^{MSI} cryptocurrencies tend to underperform the lowest-β^{MSI} cryptocurrencies in the short term. The highest performing assets appear to lie in the moderate β^{MSI} range, suggesting a sweet spot of sentiment sensitivity where cryptocurrencies are sensitive enough to benefit from sentiment but not overly exposed to emotional volatility. However, crypto-level analysis shows that, when controlling for crypto-specific characteristics such as size momentum, volatility and liquidity, the association between β^{MSI} and returns appears to be positive. Hence, we can conclude that music sentiment, as a collective mood proxy, does not uniformly influence cryptocurrencies. The effect depends on the level of sentiment sensitivity, the investment horizon and divergence from fundamentals.

4.4. Robustness check

To validate the consistency of our findings and address the mixed results observed in the original analysis, we perform a robustness check using the music sentiment index developed by Hadhri (2023). By re-evaluating both portfolio and crypto-level analyses, we test whether the predictive patterns identified in the main analysis are robust to alternative sentiment measurement methodologies.

Based on the music sentiment index of Hadhri (2023), we first computed the music sentiment betas (β_1^{MSI}) of all cryptocurrencies and then used this index for further testing. The portfolio-level analysis (Table 6) reaffirms the initial findings in Table 1. It shows that the highest-β_1^{MSI} portfolio tends to underperform the lowest-β_1^{MSI} portfolio and that the excess return of the H-L portfolio is of −0.001 per week. Subsequently, we adjust the portfolio excess returns to the three-factor cryptocurrency model and the results remain similar to the main results. The H-L per week risk-adjusted return is −0.002, suggesting that cryptocurrencies with the highest β_1^{MSI} underperform cryptocurrencies with the lowest β_1^{MSI}. In addition, no clear pattern of risk-return tradeoff emerges, as portfolios with high music sentiment beta (positive or negative) do not have the highest returns. Interestingly, Portfolio 4, which has a moderately negative sentiment beta of −0.179, generates the highest excess return of 0.157 per week and the highest alpha of 0.122 per week. This reinforces earlier evidence that a sweet spot in sentiment sensitivity may exist and that cryptocurrencies too sensitive (positively or negatively) to collective mood may not be rewarded by commensurate returns.

Next, we explore the persistence of β_1^{MSI}. The results in Table 7 are similar to those reported in Table 2, where β_1^{MSI} tends to reverse over time. The relationship between past and future β_1^{MSI} appears inconsistent and weak especially when controlling for lagged β_1^{MSI} and other lagged characteristics. This confirms earlier findings (Table 2) that music sentiment beta is not a stable asset characteristic but

Table 6
Alternate music sentiment beta – Univariate portfolios of cryptocurrencies.

	β_1^{MSI}	VW excess returns	Alphas
Low	−1.617	0.007	0.018
		(0.671)	*(1.599)*
2	−0.277	0.004	0.009
		(0.625)	*(1.251)*
3	−0.173	0.010	0.015
		(0.740)	*(1.048)*
4	−0.179	0.157	0.122
		(1.120)	*(0.829)*
5	−0.034	0.018	0.014
		(1.038)	*(0.741)*
6	0.039	−0.003	−0.003
		(−0.538)	*(−0.419)*
7	0.134	0.007	0.007
		(0.357)	*(0.360)*
8	0.229	0.019	0.020
		(1.996)	*(2.005)*
9	0.353	0.012	0.017
		(1.566)	*(2.118)*
High	1.465	0.007	0.017
		(0.755)	*(1.834)*
H-L		−0.001	−0.002
		(−0.069)	*(−0.154)*

This table presents the excess returns and alphas (adjusted with the three-factor model) of cryptocurrency deciles sorted by music sentiment beta (β_1^{MSI}) and formed weekly, from March 2018 to April 2023. The decile 1 portfolio (low) consists of cryptocurrencies with the lowest β_1^{MSI}, whereas the decile 10 portfolio (high) consists of cryptocurrencies with the highest β^{MSI}. All value-weighted excess returns and alphas are one week ahead of the portfolio-formation period. The final row shows the differences in weekly excess returns and alphas between deciles ten and one. Newey-West (1987) adjusted t-statistics are presented in parentheses.

Table 7
Persistence of alternate music sentiment beta.

t-month ahead β_1^{MSI}	Univariate Predictive Regressions	Controlling for Lagged Variables
t = 1	−0.00001	0.041
	(−0.654)	*(3.570)*
t = 2	−0.007	−0.011
	(−2.031)	*(−1.418)*
t = 3	−0.001	0.007
	(−1.372)	*(0.455)*
t = 4	−0.00005	−0.034
	(−0.659)	*(−5.303)*
t = 5	−0.004	−0.077
	(−5.106)	*(−4.693)*

To examine the persistence of music sentiment beta (β_1^{MSI}), we conducted crypto-level cross-sectional regressions of β_1^{MSI} on its own lagged values and lagged cross-sectional predictors from March 2018 to April 2023. The first column reports the average slope coefficients from univariate Fama-MacBeth regressions of one-month to five-month-ahead β_1^{MSI} on lagged β_1^{MSI}. The last column presents the average slope coefficients from multivariate Fama-MacBeth regressions that control for additional lagged variables: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD). Newey-West (1987) adjusted t-statistics are presented in parentheses.

rather a time-varying behavioral signal and that relying on its historical values for long-term investment strategies may be irrational.

Later, we checked the average characteristics of cryptocurrencies, and a similar profile was reported in Table 8, as reported in Table 3. Cryptocurrencies with high β_1^{MSI} are associated with higher market beta, lower momentum, lower volatility, and potentially greater liquidity. These profiles suggest that market leading, less volatile and more liquid assets may attract greater sentiment-driven trading. However, this exposure does not guarantee superior returns.

Subsequently, we run crypto-level cross-sectional regressions. Surprisingly, unlike the main results where the crypto-level regressions revealed a positive association between music sentiment beta and one-week-ahead cryptocurrency returns after controlling for fundamentals, the robustness test (Table 9) shows a statistically significant negative relationship in both univariate and multivariate settings. Hence, crypto-level findings are in line with the portfolio-level findings. Although the small magnitude of the average slope coefficient $\beta_{1_{i,t}}^{MSI}$ (nearly zero), the high significance confirms that music sentiment beta is negatively linked to short-term return expectations, even after controlling for crypto-specific characteristics. This evidence is consistent with the results of Edmans et al. (2022) showing that music sentiment is negatively correlated with next-week stock returns, and supporting sentiment-induced

Table 8
Average cryptocurrencies characteristics based on alternate music sentiment beta.

Variable	1	2	3	4	5	6	7	8
Intercept	−0.023	0.008	−0.007	0.062	0.097	0.027	−0.009	0.515
	(−0.257)	*(0.036)*	*(−0.149)*	*(0.921)*	*(1.304)*	*(0.492)*	*(−0.100)*	*(1.248)*
BETA	0.291							0.355
	(0.771)							*(0.870)*
MCAP		−0.001						−0.023
		(−0.060)						*(−1.021)*
MOMr2			−0.072					−0.348
			(−2.663)					*(−1.775)*
RETVOL				−0.706				−3.548
				(−1.574)				*(−1.262)*
IDIOVOL					−0.946			−1.111
					(−1.845)			*(−0.693)*
MAXRET						−0.165		1.355
						(−1.063)		*(1.034)*
DAMIHUD							−0.665	−0.654
							(−0.534)	*(−0.618)*

This table presents the time-series averages of the slope coefficients obtained from regressions of music sentiment beta (β_1^{MSI}) on various crypto-level characteristics and risk factors from March 2018 to April 2023.Weekly cross-sectional regressions were conducted using the following econometric specification and its nested versions:

$$\beta_{1_{i,t}}^{MSI} = .\lambda_{0,t} + \lambda_{1,t}X_{i,t} + \varepsilon_{i,t}$$

where $\beta_{1_{i,t}}^{MSI}$ is the music sentiment beta of crypto i in month t, $\lambda_{0,t}$ and $\lambda_{1,t}$ are time-varying coefficients, $X_{i,t}$ is a vector of crypto-specific variables observable at time t for cryptocurrency i, and $\varepsilon_{i,t}$ is the error term.The crypto-specific variables included in $X_{i,t}$ are: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD). Newey-West (1987) adjusted t-statistics are presented in parentheses.

Table 9
Alternate music sentiment beta − Fama-MacBeth cross-sectional regressions.

Variable	1	2	3	4	5	6	7	8
Intercept	0.022	0.022	0.014	0.011	0.009	0.008	0.019	0.041
	(5.567)	*(5.559)*	*(3.334)*	*(2.188)*	*(1.481)*	*(1.262)*	*(1.896)*	*(6.474)*
β_1^{MSI}	−0.00001	0.00022	−0.001	−0.002	0.000	−0.001	−0.007	−0.003
	(−5.354)	*(0.320)*	*(−3.008)*	*(−3.136)*	*(−0.546)*	*(−1.213)*	*(−3.681)*	*(−3.424*
)BETA		0.00035	−0.00010	0.002	0.001	0.001	0.00028	−0.001
		(0.490)	*(−0.437)*	*(4.506)*	*(2.498)*	*(1.034)*	*(0.378)*	*(−1.164)*
MCAP			−0.074	−0.010	−0.053	−0.046	−0.015	−0.007
			(−3.396)	*(−3.447)*	*(−3.957)*	*(−3.816)*	*(−1.611)*	*((−1.477)*
MOMr2				0.001	0.010	0.011	−0.020	0.00041
				(5.133)	*(3.596)*	*(3.353)*	*(−3.501)*	*0.120)*
RETVOL					0.004	0.005	0.007	−0.001
					(1.323)	*(2.030)*	*(4.282)*	*(−0.505)*
IDIOVOL						0.00005	−0.00007	0.00002
						(0.992)	*(−3.054)*	*(1.610)*
MAXRET							0.011	−0.010
							(2.480)	*(−3.831)*
DAMIHUD								0.000
								(−0.380)
Adj R^2	0.10 %	0.14 %	0.19 %	0.27 %	0.49 %	0.44 %	0.62 %	0.68 %

This table presents the results of the Fama-Macbeth regression. The cross-sectional regression was run using crypto-level one-week-ahead returns on music sentiment beta ($\beta_{1_{i,t}}^{MSI}$) and other crypto-specific characteristics (added one at a time as a control variable) from March 2018 to April 2023. The crypto-specific variables included in $X_{i,t}$ are: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD). This table reports the time-series averages of coefficients and adjusted R^2 from weekly regressions, and the corresponding Newey-West (1987) adjusted t-statistics are presented in parentheses.

temporary mispricing theory.

Finally, results in Table 10 show that this negative relationship between $\beta_{1_{i,t}}^{MSI}$ and subsequent cryptocurrency returns is persistent across various time horizons. In the short-term (2–4 weeks), medium-term (7th week), and long-term (11–12 weeks), high sentiment sensitivity continues to signal lower expected returns, reinforcing behavioral interpretation that mood-based sentiment does not lead to sustained excess returns but may predict overvaluation and underperformance.

Therefore, based on the main portfolio-level findings and the portfolio- and crypto-level findings of the robustness check analysis, we report a negative relationship between music sentiment beta and cryptocurrency returns (one-week-ahead returns). It is important to note that this relationship holds in both the short and long term.

5. Conclusion

This paper examines the impact of music sentiment on the cross-sectional pricing of cryptocurrencies. Music sentiment is quantified using Spotify mood metrics, which capture global trends in collective mood based on music listening behavior. By estimating the exposure of cryptocurrencies to music-based sentiment, measured through the music sentiment beta.

β^{MSI}, we show that sentiment sensitivity explains a significant portion of the future cross-sectional variation in cryptocurrency returns.

Our univariate portfolio-level analyses reveal that cryptocurrencies with low β^{MSI} outperform those with high β^{MSI}. We find that the portfolio that is long in cryptocurrencies with the highest music sentiment beta and short in those with the lowest music sentiment beta generates a negative average excess return. This music sentiment premium is driven by the underperformance of highly sentiment-sensitive cryptocurrencies (with positive β^{MSI}) and the outperformance of sentiment-averse cryptocurrencies (with negative β^{MSI}) and is consistent with theoretical predictions, suggesting that sentiment-averse investors require additional compensation to hold cryptocurrencies with negative sentiment beta, while they are willing to pay a premium for those with positive sentiment beta. When adjusting returns using a three-factor cryptocurrency model, the results remain robust. We find that the best risk-return tradeoff is concentrated in the middle decile of the β^{MSI} distribution (i.e., portfolio 4), suggesting a potential sweet spot in sentiment sensitivity where cryptocurrencies are neither overly reactive nor sentiment-immune. Interestingly, our results also show that the 8th and 9th decile portfolios generate a statistically significant weekly risk-adjusted return of 3.80 % and 1.50 %, respectively. These results support a nonlinear pattern where sentiment exposure attracts investors without excessive volatility.

To overcome the limitations of portfolio sorting, we employ Fama-MacBeth (1973) cross-sectional regressions at the individual cryptocurrency level. In the univariate specifications, β^{MSI} is significantly negatively associated with two to five-week-ahead returns. After controlling for well-known crypto-specific factors such as size, market, momentum, market capitalization, liquidity, idiosyncratic volatility, market volatility beta, and systemic risk, the relationship reverses and becomes significantly positive at the two- and five-week horizons, indicating that music sentiment beta captures return variations beyond those explained by traditional risk factors.

Table 10
Long-term predictive power of alternate music sentiment beta.

	Intercept	β_1^{MSI}	BETA	MCAP	MOMr2	RETVOL	IDIOVOL	MAXRET	DAMIHUD	Adj R2
t + 2	0.019	−0.004	−0.001	−0.037	−0.018	0.004	0.00004	0.008	0.0000	0.95 %
	(4.741)	*(−2.714)*	*(−2.599)*	*(−3.653)*	*(−4.450)*	*(2.787)*	*(2.403)*	*(2.057)*	*(−1.788)*	
t + 3	0.021	−0.001	−0.0003	−0.010	−0.0003	−0.0003	−0.0001	−0.001	0.0000	0.48 %
	(5.334)	*(−1.660)*	*(−0.656)*	*(−1.350)*	*(−0.054)*	*(−0.080)*	*(−1.349)*	*(−0.168)*	*(−2.150)*	
t + 4	0.022	−0.00001	−0.0004	−0.002	−0.004	0.001	−0.00004	0.002	0.0000	0.72 %
	(5.442)	*(−0.006)*	*(−0.598)*	*(−0.157)*	*(−0.321)*	*(0.912)*	*(−0.366)*	*(0.565)*	*(0.118)*	
t + 5	0.022	0.001	0.000	0.003	−0.012	−0.002	0.000	−0.008	0.000	0.51 %
	(5.445)	*(0.527)*	*(−0.244)*	*(0.553)*	*(−1.365)*	*(−0.912)*	*(0.951)*	*(−2.009)*	*(−2.150)*	
t + 6	0.022	0.001	0.001	−0.005	0.001	0.003	0.000	0.004	0.000	0.74 %
	(5.531)	*(0.278)*	*(1.650)*	*(−0.453)*	*(0.120)*	*(1.559)*	*(2.840)*	*(1.440)*	*(1.659)*	
t + 7	0.209	−0.003	0.001	−0.001	−0.016	0.001	0.000	−0.001	0.000	0.51 %
	(5.200)	*(−2.517)*	*(0.950)*	*(−0.348)*	*(−1.305)*	*(1.780)*	*(−0.721)*	*(−0.355)*	*(2.596)*	
t + 8	0.024	0.001	0.000	0.021	0.025	−0.003	0.000	−0.004	0.000	0.61 %
	(5.808)	*(1.287)*	*(0.000)*	*(2.143)*	*(3.038)*	*(−2.343)*	*(1.113)*	*(−1.282)*	*(1.619)*	
t + 9	0.019	0.000	0.002	−0.028	−0.016	0.002	0.000	−0.002	0.000	0.78 %
	(4.839)	*(0.106)*	*(2.383)*	*(−2.440)*	*(−1.239)*	*(0.852)*	*(−0.488)*	*(−0.328)*	*(2.076)*	
t + 10	0.022	0.001	0.002	−0.017	0.003	−0.003	0.000	−0.004	0.000	0.78 %
	(5.368)	*(0.899)*	*(3.347)*	*(−2.671)*	*(0.249)*	*(−2.349)*	*(0.388)*	*(−1.663)*	*(−1.165)*	
t + 11	0.022	−0.001	0.001	0.002	0.001	−0.001	0.000	−0.002	0.000	0.42 %
	(5.437)	*(−0.676)*	*(0.794)*	*(0.193)*	*(0.216)*	*(−1.655)*	*(0.542)*	*(−1.683)*	*(−1.206)*	
t + 12	0.023	−0.002	0.003	−0.005	0.005	−0.001	0.000	−0.001	0.000	0.41 %
	(5.566)	*(−1.988)*	*(3.305)*	*(−1.256)*	*(0.808)*	*(−0.768)*	*(−0.528)*	*(−0.159)*	*(1.331)*	

This table presents the results from regressing weekly excess returns, from two to twelve weeks ahead, against music sentiment beta (β_1^{MSI}) after controlling for all other control variables. The other control variables are: market beta (BETA), market capitalization (MCAP), past two-week return (MOMr2), return volatility (RETVOL), idiosyncratic volatility (IDIOVOL), maximum daily return (MAXRET), and illiquidity (DAMIHUD). Newey-West (1987) adjusted t-statistics are presented in parentheses. The sample period is from March 2018 to April 2023.

Further, our results reveal that cryptocurrencies with high β^{MSI} tend to have higher market beta, lower size, lower momentum, and lower volatility.

While results show a positive relationship with one-week-ahead returns, the music sentiment premium exhibits a reversal over time, indicating its nonlinear, time-varying nature. This finding aligns with sentiment-induced temporary mispricing theories and reflects short-lived investor sentiment dynamics. The relationship between sentiment betas and returns strengthens when control variables are included, underscoring the role of music sentiment as a distinct factor in predicting cryptocurrency returns, even over extended periods. The relationship is significant when predicting 2-, 3-, 9-, and 12-week-ahead returns, which is consistent with investor attention cycles theory suggesting delayed performance effects.

A comprehensive robustness check confirms the consistency of our main findings. Specifically, we find that both portfolio- and crypto-level analyses show that cryptocurrencies with higher β^{MSI} underperform across short-, medium-, and even long-term horizons. These findings align with Edmans et al. (2022), who report a similar negative relationship between music sentiment and returns in equity markets. Thus, our results extend this phenomenon into the cryptocurrency space and highlight the generalizability of music sentiment-induced mispricing across asset classes.

Given that music sentiment closely reflects individual mood fluctuations, this index can provide an accurate measure of time-series variations in sentiment and associated investment opportunities. The fact that cryptocurrencies' exposure to music sentiment successfully predicts future cross-sectional cryptocurrency returns also suggests that the music sentiment beta serves as a reliable proxy for sentiment-driven investment risk in conditional asset pricing models with time-varying sentiment. Investors and researchers can better understand how emotional dynamics influence asset pricing in decentralized markets by incorporating mood-based sentiment measures.

Additional tests could be conducted to further validate the findings. For instance, as potential avenues for future research, we suggest performing subsample analyses across different market conditions and cryptocurrency characteristics such as by market capitalization (large vs. small), time periods (e.g., bull vs. bear markets), and volatility regimes.

CRediT authorship contribution statement

Sinda Hadhri: Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Mehak Younus:** Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Muhammad Abubakr Naeem:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Larisa Yarovaya:** Writing – review & editing, Supervision, Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

We are thankful for the participants of the 7th Cryptocurrency Research Conference, held on 23-24 September 2024 at Zayed University, Dubai, UAE, for providing helpful comments and suggestions on the earlier version of our paper. We are also thankful to the editors, guest editors and two anonymous reviewers for their comments and feedback.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5 (1), 31–56.
Andreou, C.K., Lambertides, N., Panayides, P.M., 2021. Distress risk anomaly and misvaluation. Br. Account. Rev. 53 (5), 100972.
Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Finance 61 (1), 259–299.
Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: International and further US evidence. J. Financ. Econ. 91 (1), 1–23.
Akyildirim, E., Corbet, S., Sensoy, A., Yarovaya, L., 2020. The impact of blockchain related name changes on corporate performance. Finance 65, 101759.
Azqueta, G.A., Hirschbuehl, D., Onorante, L., Saiz, L., 2023. Sources of economic policy uncertainty in the euro area. Eur. Econ. Rev. 152, 104373.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61, 1645–1680.
Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21, 129–151.
Baker, M., Wurgler, J., Yuan, Y., 2012. Global, local, and contagious investor sentiment. J. Financ. Econ. 104 (2), 272–287.
Bali, T.G., Brown, S.J., Tang, Y., 2017. Is economic uncertainty priced in the cross-section of stock returns? J. Financ. Econ. 126 (3), 471–489.
Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. J. Financ. Econ. 99 (2), 427–446.
Banz, R.W., 1981. The relationship between return and market value of common stocks. J. Financ. Econ. 9 (1), 3–18.
Barber, B.M., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21 (2), 785–818.
Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. J. Financ. Econ. 49 (3), 307–343.
Benedetti, H., Kostovetsky, L., 2021. Digital tulips? returns to investors in initial coin offerings. Finance 66, 101786.
Biais, B., Bisière, C., Bouvard, M., Casamatta, C., Menkveld, A.J., 2023. Equilibrium bitcoin pricing. J. Financ. 78 (2), 967–1014.
Bianchi, D., Babiak, M., Dickerson, A., 2022. Trading volume and liquidity provision in cryptocurrency markets. J. Bank. Financ. 142, 106547.
Bindseil, U., and Schaaf, J. (2024). ETF approval for bitcoin – the naked emperor's new clothes. https://www.ecb.europa.eu/press/blog/date/2024/html/ecb.blog202402220929f86e23.en.html.
Bori, N., Shakhnov, K., 2021. The cross-section of cryptocurrency returns. Rev Asset Pric Stud 12 (3), 667–705.
Bourghelle, D., Jawadi, F., Rozin, P., 2022. Do collective emotions drive bitcoin volatility? a triple regime switching vector approach. J. Econ. Behav. Organ. 196, 294–306.
Brauneis, A., Mestel, R., Riordan, R., Theissen, E., 2021. How to measure the liquidity of cryptocurrency markets? J. Bank. Financ. 124, 106041.
Buffett, W., 2018. Warren buffett explains one thing people still don't understand about bitcoin. https://www.cnbc.com/2018/05/01/warren-buffett-bitcoin-isnt-an-investment.html.
Cai, C.X., Zhao, R., 2024. Salience theory and cryptocurrency returns. J. Bank. Financ. 159, 107052.
Chang, S., Chen, S., Chou, R., Lin, Y., 2008. Weather and intraday patterns in stock returns and trading activity. J. Bank. Financ. 32, 1754–1766.
Cheah, E.T., Fry, J., 2015. Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. Econ. Lett. 130, 32–36.
Chen, Z., Lien, D., Ln, Y., 2021. Sentiment: the bridge between financial markets and macroeconomy. Journal of Economic Behavior and Organizations 188, 1177–1190.
Chiu, J., Koeppl, T.V., 2019. Blockchain-based settlement for asset trading. Rev. Financ. Stud. 32 (5), 1716–1753.
Clynes, M., 1977. Sentics: the touch of emotions. Anchor Press.
Clynes, M., 1980. The communication of emotions: theory of sentics. Theories of Emotion 271–301.
Colombo, J.A., Yarovaya, L., 2024. Are crypto and non-crypto investors alike? evidence from a comprehensive survey in Brazil. Technol. Soc. (76).
Cong, L.W., Li, Y., Wang, N., 2021. Tokenomics: dynamic adoption and valuation. Rev. Financ. Stud. 34 (3), 1105–1155.
Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. J. Financ. 66 (5), 1461–1499.
Da, Z., Engelberg, J., Gao, P., 2015. The sum of all FEARS investor sentiment and asset prices. Rev. Financ. Stud. 28 (1), 1–32.
De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Noise trader risk in financial Markets. J. Polit. Econ. 98 (4), 703–738.
Dias, I.K., Fernando, J.R., Fernando, P.N.D., 2022. Does investor sentiment predict bitcoin return and volatility? a quantile regression approach. Int. Rev. Financ. Anal. 84, 102383.
Dhawan, A., Putniņš, T.J., 2022. A new wolf in town? pump-and-dump manipulation in cryptocurrency markets. Eur. Finan. Rev. 27 (3), 935–975.
Edmans, A., Garcia, D., Norli, O., 2007. Sport sentiment and stock returns. J. Financ. 4, 1967–1998.
Edmans, A., Fernandez-Perez, A., Garel, A., Indriawan, I., 2022. Music sentiment and stock returns around the world. J. Financ. Econ. 145, 234–254.
Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Finance 47 (2), 427–465.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116 (1), 1–22.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. J. Political Econ. 81 (3), 607–636.
Fang, J., Zhang, Y., 2023. Idiosyncratic volatility and return: a finite mixture approach. Br. Account. Rev. 101261.
Farag, H., Luo, D., Yarovaya, L., Zieba, D., 2025. Returns from liquidity provision in cryptocurrency markets. J. Bank. Financ. forthcoming.
Fernandez-Perez, A., Garel, A., Indriawan, I., 2020. Music sentiment and stock returns. Econ. Lett. 192, 109260.
Frazzini, A., Pedersen, L.H., 2014. Betting against beta. J. Financ. Econ. 111 (1), 1–25.
Gabrielsson, A., Juslin, P.N., 1996. Emotional expression in music performance: between the performer's intention and the listener's experience. Psychol. Music 24, 68–91.
García, D., 2013. Sentiment during recessions. J. Financ. 68 (3), 1267–1300.
Garland, E.L., Fredrickson, B., Kring, A.M., Johnson, D.P., Meyer, P.S., Pen, D.L., 2010. Upward spirals of positive emotions counter downward spirals of negativity: insights from the broaden and build theory and effective neuroscience on the treatment of emotion dysfunctions and deficits in psychopathology. Clin. Psychol. Rev. 30 (7), 849–864.
Greenberg, D.M., Baron-Cohen, S., Stillwell, D.J., Kosinski, M., Rentfrow, P.J., 2015. Musical preferences are linked to cognitive styles. PLoS One 10.
Greenberg, D.M., Kosinski, M., Stillwell, D.J., Monteiro, B.L., Levitin, D.J., Rentfrow, P.J., 2016. The song is you: preferences for musical attribute dimensions reflect personality. Soc. Psychol. Personal. Sci. 7 (6), 597–605.
Hackethal, A., Hanspal, T., Lammer, D.M., Rink, K., 2021. The characteristics and portfolio behavior of bitcoin investors: evidence from indirect cryptocurrency investments. Eur. Finan. Rev. 26 (4), 855–898.

Hadhri, S., 2023. Do cryptocurrencies feel the music? Int. Rev. Financ. Anal. 89, 102779.
Hafner, C.M., 2018. Testing for bubbles in cryptocurrencies with time-varying volatility. J. Financ. Economet. 18 (2), 233–249.
Hansen, P.R., Kim, C., Kimbrough, W., 2022. Periodicity in cryptocurrency volatility and liquidity. J. Financ. Economet. 22 (1), 224–251.
Härdle, W.K., Harvey, C.R., Reule, R.C.G., 2020. Understanding cryptocurrencies. J. Financ. Economet. 18 ((2), 181–208.
Hautsch, N., Scheuch, C., Voigt, S., 2024. Building trust takes time: limits to arbitrage for blockchain-based assets. Review of Finance rfae004.
Hirshleifer, D., Shumway, T., 2003. Good day sunshine: stock returns and the weather. J. Financ. 58, 1009–1032.
Hong, H., Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset Markets. J. Financ. 54 (6), 2143–2184.
Huang, D., Jiang, F., Tu, J., Zhou, G., 2014. Investor sentiment aligned: a powerful predictor of stock returns. Rev. Financ. Stud. 28 (3), 791–837.
Ince, O.S., Porter, R.B., 2006. Individual equity return data from Thomson Datastream: Handle with care! J. Financ. Res. 29 (4), 463–479.
Isen, A.M., Shalker, T.E., Clark, M., Karp, L., 1978. Effect, accessibility of material in memory, and behavior: a cognitive loop? J. Pers. Soc. Psychol. 36 (1), 1–12.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. J. Finance 48 (1), 65–91.
Jiao, P., Veiga, A., Walther, A., 2020. Social media, news media and the stock market. Journal of Economic Behavior and Organizations 176, 63–90.
Juslin, P.N., Laukka, P., 2004. Expression, perception and induction of musical emotions: a review and a questionnaire study of everyday listening. Journal of New Music Research 33 (3), 217–238.
Kaiser, L., Stöckl, S., 2020. Cryptocurrencies: herding and the transfer currency. Financ. Res. Lett. 33, 101214.
Kaplanski, G., Levy, H., 2010. Sentiment and stock prices: the case of aviation disasters. J. Financ. Econ. 95, 174–201.
Kaplanski, G., Levy, H., Veld, C., Veld-Merkoulova, Y., 2013. Do happy people make optimistic investors? J. Financ. Quant. Anal. 50 (1/2), 145–168.
Karau, S., 2023. Monetary policy and bitcoin. J. Int. Money Financ. 137, 102880.
Knippenberg, D., Kooij-de Bode, H.J.M., van Ginkel, W.P., 2010. The interactive effects of mood and trait negative affect in group decision making. Organ. Sci. 21 (3), 593–801.
Koelsch, S., 2014. Brain correlates of music-evoked emotions. Nat. Rev. Neurosci. 15, 170–180.
Kogan, S., Makarov, I., Niessner, M., Schoar, A., 2024. Are cryptos different? evidence from retail trading. J. Financ. Econ. 159, 103897.
Kostopoulos, D., Meyer, S., 2018. Disentangling investor sentiment: mood and household attitudes. J. Econ. Behav. Organ. 155, 28–78.
Kostopoulos, D., Meyer, S., Uhr, C., 2020. Google search volume and individual investor trading. J. Financ. Mark. 49, 100544.
Kraaijeveld, O., Smedt, J.D., 2020. The predictive power of public twitter sentiment for forecasting cryptocurrency prices. J. Int. Financ. Mark. Inst. Money 65, 101188.
Landis, C., Skouras, S., 2021. Guidelines for asset pricing research using international equity data from Thomson Reuters Datastream. J. Bank. Finance 130, 106128.
Lanfear, M.G., Lioui, A., Siebert, M.G., 2019. Market anomalies and disaster risk: evidence from extreme weather events. J. Financ. Mark. 46, 100477.
Li, Y., Goodell, J.W., Shen, D., 2021. Comparing search-engine and social-media attentions in finance research: evidence from cryptocurrencies. Int. Rev. Econ. Financ. 75, 723–746.
Lim, H.A., Park, H., 2018. The effect of music on arousal, enjoyment, and cognitive performance. Psychol. Music 47 (4), 539–550.
Liu, Y., Tsyvinski, A., 2021. Risks and returns of cryptocurrency. Rev. Financ. Stud. 34 (6), 2689–2727.
Liu, Y., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. J. Financ. 77 (2), 1133–1177.
Loewenstein, G., Weber, E.U., Hsee, C.K., Welch, N., 2001. Risk as feelings. Psychol. Bull. 127 (2), 267–286.
Loewenstein, G., Lerner, J.S., 2003. The role of affect in decision making. Oxford University Press, Handbook of Affective Sciences.
Long, S.C., Lucey, B., Xie, Y., Yarovaya, L., 2022. "I just like the stock": the role of reddit sentiment in the GameStop share rally. The Financial Review 58 (1), 19–37.
Lucey, B.M., Vigne, S.A., Yarovaya, L., Wang, Y., 2022. The cryptocurrency uncertainty index. Financ. Res. Lett. 45, 102147.
Mahmoudi, N., Docherty, P., Melia, A., 2022. Firm-level investor sentiment and corporate announcement returns. J. Bank. Financ. 144, 106586.
Makarov, I., Schoar, A., 2020. Trading and arbitrage in cryptocurrency markets. J. Financ. Econ. 135 (2), 293–319.
Manela, A., Moreira, A., 2017. News implied volatility and disaster concerns. J. Financ. Econ. 123 (1), 137–162.
Naeem, M.A., Mbarki, I., Shahzad, S.J.H., 2021a. Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears. Int. Rev. Econ. Finance 73, 496–514.
Naeem, M.A., Mbarki, I., Suleman, M.T., Vo, X.V., Shahzad, S.J.H., 2021b. Does Twitter happiness sentiment predict cryptocurrency? Int. Rev. Econ. Finance 21 (4), 1529–1538.
Nguyen, C.M., Koenigs, M., Yamada, T.H., Teo, S.H., Cavanaugh, J.E., Tranel, D., Denburg, N.L., 2011. Trustworthiness and negative affect predict economic decision making. J. Cogn. Psychol. 23 (6), 748–759.
Ortega, A.R., Ramirez, E., Colmenero, J.M., Garcia-Viedma, A., 2012. Negative affect, decision making and attentional networks. J. Atten. Disord. 21 (3), 247–253.
Recours, R., Aussaguel, F., Trujillo, N., 2009. Metal music and mental health in France. Cult. Med. Psychiatry 33 (3), 473–488.
Rentfrow, P.J., Gosling, S.D., 2003. The do re mi's of everyday life: the structure and personality correlates of music preferences. J. Pers. Soc. Psychol. 84, 1236.
Sabouni, H., 2018. The rhythm of markets. Claremont Graduate University Unpublished Working Paper.
Saunders, E., 1993. Stock prices and wall street weather. Am. Econ. Rev. 83, 1337–1345.
Schwarz, N., Clore, G.L., 1983. Mood, misattribution, and judgments of wellbeing: informative and directive functions of effective states. J. Pers. Soc. Psychol. 45, 513–523.
Shiller, R.J., 2017. Narrative economics. Am. Econ. Rev. 107 (4), 967–1004.
Sockin, M., Xiong, W., 2023. A model of cryptocurrencies. Manag. Sci. 69 (11), 6684–6707.
Stambaugh, R.F., Yu, J., Yuan, Y., 2012. The short of it: investor sentiment and Anomalies. J. Financ. Econ. 104 (2), 288–302.
Tetlock, P., 2007. Giving content to investor sentiment: the role of media in the stock market. J. Financ. 62, 1139–1168.
Trimborn, S., Li, M., Härdle, W.K., 2019. Investing with cryptocurrencies—a liquidity constrained investment approach. J. Financ. Economet. 18 (2), 280–306.
Urquhart, A., 2018. What causes attention of bitcoin? Econ. Lett. 166, 40–44.
Van Dijk, M.A., 2011. Is size dead? A review of the size effect in equity returns. J. Bank. Financ. 35 (12), 3263–3274.
Vuilermier, P., Trost, W., 2015. Music and emotions: from enchantment to entrainment. Ann. N. Y. Acad. Sci. 1337 (1), 212–222.
Wooten, M.A., 1992. The effects of heavy metal music on effects shifts of adolescents in an inpatient psychiatric setting. Music. Ther. Perspect. 10 (2), 93–98.
Yao, S., Kong, X., Sensoy, A., Akyldrim, E., Cheng, F., 2021. Investor attention and idiosyncratic risk in cryptocurrency markets. Eur. J. Financ. 1–19.
Yelowitz, A., Wilson, M., 2015. Characteristics of bitcoin users: an analysis of Google search data. Appl. Econ. Lett. 22 (13), 1030–1036.
Zhang, W., Li, Y., Xiong, X., Wang, P., 2021. Downside risk and the cross-section of cryptocurrency returns. J. Bank. Financ. 133, 106246.