The Sound of Cryptos

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Abstract

This paper explores the mood-induced mispricing phenomenon in the cryptocurrency market by using Spotify music sentiment. Daily country-level music sentiments are aggregated into a global sentiment index by using Google Search Volume Index to reflects the mood of cryptocurrency investors directly. The authenticity of the music sentiment index is firstly validated by regressing against FEARS index developed by Da, Engelberg, and Gao (2015), and then the commercial crypto sentiment index "Crypto Fear & Greed Index". The results support that the aggregated music sentiment index is positively correlated with the sum of contemporaneous and next-day return, then reverse on the following two days. These findings are consistent with temporary sentiment-induced mispricing. It is also found that the aggregated music sentiment index is positively correlated with cryptocurrency market volatility and liquidity.

JEL Classification: G12, G14, G41
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1. Introduction

The cryptocurrency market has been well-known for its volatility and high exposure to market sentiment. Some notable events are the 2017 cryptocurrency market boom and a series of extreme price fluctuations after Elon Musk's tweets. These irrational price movements are hardly captured by traditional efficient market hypothesis or asset pricing methods and thus required novel analytical methods. Examples of well-studied risk factors in cryptocurrency pricing include network effects (Cong et al., 2020; Biais et al., 2018) and investor attention (Liu & Tsyvinski, 2021). Liu et al. (2022) also construct a three-factor model, namely market, size and momentum factors, that can explain a series of cryptocurrency return predictors. Another branch of cryptocurrency pricing studies dedicates to sentimental and textual analysis by using machine and statistical learning methods (e.g. Nasekin & Chen, 2020; Chen et al., 2019). These studies utilize cryptocurrency-specific social media posts or news to evaluate collective attitude of traders and investors towards specific cryptocurrencies or the entire cryptocurrency market. Yet, few papers studied mood-induced mispricing in cryptocurrency market, which investors misprice an asset owing to their personal mood instead of an irrational bearish/bullish view on an asset.

The phenomenon of mood-induced mispricing is well-established in the equity market. Some examples of mood-induced mispricing are weather and cloud cover (Hirshleifer & Shumway, 2003; Wiggins, 2015); and seasonality (Hirshleifer et al., 2020). Edmans et al. (2021) suggest a novel way to evaluate investor mood by using Spotify music data which they argue that is an endogenous factor as music choices reflect investors' actual mood directly[2] without the fuss to determine what

[2] Edmans et al. (2021) has also addressed the concern of music is used in neutralizing mood instead of reflecting it associating it with mood proxies.

and how an exogenous event impacts mood. Thus, this paper aims to explore music data to study mood-induced mispricing.

Similar to Edmans et al. (2021) paper, music data is retrieved from Spotify. As of the end of 2021, Spotify is the largest online music platform in the world with 406 million[3] monthly active users across more than 180 countries. The immense coverage of this dataset ensures that there is a significant population of Spotify users in each country. Moreover, there are around 55% of Spotify users[4] and 58% of cryptocurrency traders[5] with age below 35. The comparable demographic further supports that there is a high chance that Spotify users overlap with cryptocurrency traders and Spotify data can indeed represent the financial market participants. In addition, Spotify provides a daily top-200 song chart for each country as well as valence scores which represent songs' sentiment. With these data, a daily music sentiment index can be constructed for each country. Yet, per country cryptocurrency trading data is extremely hard, if not impossible, to get. In this regard, to make holistic and reasonable analysis with music and cryptocurrency data, the music sentiment index is aggregated[6] into a global index weighted by per country Google Search Volume Index of the word "Bitcoin" which represents the per country investor attention on cryptocurrency (Liu & Tsyvinski, 2021).

The main analysis of this paper focuses on the correlation between music sentiment and cryptocurrency market return. It is found that music sentiment is positively and significantly associated with cryptocurrency market return. A 1.41 basis points (bps) increases in two-day

[3] As seen in the Press Release of Spotify 2021 Q4: https://s22.q4cdn.com/540910603/files/doc_financials/2021/q4/Shareholder-Letter-Q4-2021_FINAL.pdf
[4] https://www.businessofapps.com/data/spotify-statistics/
[5] https://triple-a.io/crypto-ownership/
[6] It is true that there is a "global" top-200 song chart provided by Spotify but it fails to account for country-level difference in cryptocurrency trading activity.

cryptocurrency return (103% annualized) for one standard deviation increase in music sentiment after controlling network effect, attention effect, general cryptocurrency market sentiment and autocorrelation. The increase is followed by a 1.24 bps and 0.71 bps decrease in daily return for the following two consecutive days. These results align with the temporary sentiment-induced mispricing phenomenon as documented in the previous researches (De Long et al., 1990; Baker & Wurgler, 2006). These results still hold when Bitcoin is removed from the analysis.

To further consolidate the results of this paper, the correlation between cryptocurrency market volatility and music sentiment is investigated. The result shows that absolute music sentiment is significantly and positively associated with cryptocurrency market volatility. This result is aligned with the previous studies on surging volatility under extreme investor sentiment environment owing to noise trading (De Long et al., 1990; Da, Engelberg, and Gao, 2015). This result still holds when Bitcoin is removed from the analysis. The results also support that music sentiment effect is more pronounced for larger cryptocurrencies. This can be explained by the general phenomenon that larger coins would receive more investor attention which increase chance of overreaction (Peng & Xiong, 2006; Andrei & Halser, 2015). Furthermore, it is found that liquid coins are more sensitive to sentiment. Although the relationship between liquidity and sentiment suggested by Baker et al. (2004) may not hold in cryptocurrency owing to the possibility of shorting in the market, this paper suggests the knowledge level of retail cryptocurrency traders are the cause of it as sensitivity of sentiment is lower in bearish environment.

These empirical findings contribute to the literatures of identifying and evaluating mood-induced effect in risk-based financial decisions. This is particularly important to the cryptocurrency market as it mainly comprises unsophisticated and untrained retail investors that are more easily subjected to cognitive bias (Sellier et al., 2020). Music sentiment provides a continuous, real-time, and high-frequency measure of investors' sentiment. In addition, unlike textual analysis, music's universality (Mehr et al., 2019) across countries and cultures avoid misinterpretation of lexicons across languages. This paper also contributes to the growing literatures of understanding the fledging and booming cryptocurrency market. Most current papers focus on fundamental risk factors, pricing model, and sentimental analysis of cryptocurrencies. However, few has explored the mood related psychological bias in cryptocurrency. Lastly, this paper suggests a method of aggregating country-level sentiment into a global scale for the cryptocurrency market. This is critical in the sense that many economic or financial variables in the stock market are country-level data, but cryptocurrency shares one big global market. It is critical to develop a way to aggregate past wisdom into a global scale for the study of decentralized financial products such as cryptocurrencies, NFTs, and DeFi to obtain a more holistic view.

The rest of the paper is organized as follows. In section 2, the collection of data, validation of music sentiment, and formation of control variables are discussed; in section 3, this paper's main results are reported; and section 4 concludes.

2. Hypotheses Development

Behavioural finance literatures have provided convincing evidence on the occurrence of mood-induced mispricing in the equity market, regardless of retail investors and institutional investors (Wiggins, 2015). Some researches explore the factors including weather and cloud cover which stock market returns are higher during sunny days or less cloud cover (Hirshleifer & Shumway, 2003; Wiggins, 2015); and seasonality which stock market returns are higher during certain months or weekdays (Hirshleifer et al., 2020). These positive relationship between mood and returns are consistent globally.

Mood-induced pricing, essentially, is intertemporal biased, or is an irrational decision made under the influence of a certain mood. Prior psychological researches have found that mood state does affect decision-making in prediction (Clore et al., 1994). This is because people take in a composite of affective states, including mood, when encoding memories. When they are recalled subsequently, evaluation may be biased due to past mood (Fishbein, 1963). The aforementioned mood-induced mispricing research tries to use an exogenous mood-changing factor that affects a country's mood and assumes that it also affects investors' mood, thus investment decisions. However, this approach may not capture the whole picture as a single event does not entirely dominate one's mood. Therefore, Edmans et al. (2021) suggest using country-level music data as an endogenous factor to reflect mood. This argument is in line with psychology researches of "emotion congruity" which people prefer music that reflects his current emotional state (North & Hargreaves, 1996). Hence, it is expected that if the sentiment of music chosen throughout a country is more positive, investors' mood will be more positive.

To explore the sentiment in cryptocurrency, country-level music sentiment index is aggregated into a global level index by using Google Search Volume Index of the word "Bitcoin" in each country which reflects investor attentions of cryptocurrency (Liu & Tsyvinski, 2021). Intuitively, the aggregated index can be seen as "the aggregated mood level for all the people who trade cryptocurrency across countries" and thus the positively relation between mood and music sentiment still holds after aggregation. With these being said, the following hypothesis is estalished:-

Hypothesis: Higher music sentiment is associated with high cryptocurrency market return, vice versa.

3. Data and Variables

3.1. Spotify Music Sentiment for Stocks

Since 2017, Spotify has been updating a daily top 200 songs list[7] ranked by $Streams$, which will be counted if a song is to for 30 seconds or more, for each region. 73 countries' data are retrieved from Spotify and only countries with full sample data from 1 January, 2017 are used in this study. This ends up with a sample size of 47 countries over the period from 1 January, 2017 to 19 January, 2022. This sample size contains 76,263 unique songs with 4.43 trillion total streams. On average, there are 54 million streams daily per country with around 274 thousand streams per song in each country.

Besides the top-200 songs, Spotify utilizes acoustic analysis machine learning technology powered by The Echo Test, Spotify's music intelligence division, to measure various audio features of each song. Measured audio features include music features such as tempo, time signature; as well as sentimental features such as danceability and energy. The research focus of this paper is the sentimental audio feature $Valence$, which according to Spotify's documentation[8], is "a measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence

[7] The song list can be viewed from https://spotifycharts.com/regional yet the website would be depreciated after 03 June 2022.
[8] https://developer.spotify.com/documentation/web-api/reference/#/operations/get-several-audio-features

sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry)." This measure summarizes the sentimental impact of a song brings to the listeners. It is noteworthy that this feature is solely based on the melody of a song instead of its lyrics. With these data, a stream-weighted average valence ($SWAV$) similar to that of Edmans et al. (2021) is constructed:

$$SWAV_{i,d} = \sum_{j=1}^{200} \left(\frac{Streams_{j,i,d}}{\sum_{j=1}^{j=200} Streams_{j,i,d}} \cdot Valence_{j,i,d} \right) \qquad (1a)$$

where $Streams_{j,i,d}$ is the stream in country i, on day d for song j.

To control for the country-level difference in the average level of sentiment, $Music\ Sentiment_{i,d}$ is calculated as the first difference of $SWAV_{i,d}$ such that

$$\Delta SWAV_{i,d} = SWAV_{i,d} - SWAV_{i,d-1} \qquad (1b)$$

To eliminate any extreme values and seasonality (e.g. festivals, holidays) in the $Music\ Sentiment$ index, the sentiment index is regressed against weekday dummies and month dummies in ways similar to Da, Engelberg, and Gao (2015). The residuals are obtained as the $Music\ Sentiment$ index. These series of treatments are denoted as the function R^i such that

$$Music\ Sentiment_{i,d} = R^i(\Delta SWAV_{i,d}) \qquad (1c)$$

3.2. Validating the Music Sentiment index for Stock Market

As mentioned in Edmans et al. (2021) paper, the stringency of government restrictions in response to COVID-19 taken from the University of Oxford's COVID-19 government response tracker[9] could be a measure of the sentimental effect (Terry et al., 2020) of closure due to COVID-19. According to Oxford's documentation, the stringency index captures the strictness of 8 types of 'lockdown style' policies that primarily restrict people's behaviour[10]. As the index commenced on 1st January, 2020, all preceding values are coded as 0. The first difference of the index ($\Delta COVID$) is used as a control to account for country-level difference. In addition, to control for the sentimental effect imposed by economic uncertainty and change in business conditions, the daily change of Economic Policy Uncertainty index[11] (ΔEPU) (Baker et al., 2016) and the daily change of the Aruoba, Diebold, and Scotti index[12] (ΔADS) (Aruoba et al., 2009) are used. only U.S. data are used for these indices, in contemplation that non-US countries' high frequency data of these two indices were not available, and Brusa et al. (2020) provide evidence that U.S. economic policies have a larger effect on foreign stock markets than the local ones.

Although many empirical studies use different factors for measuring investor mood (Edmans et al. 2021 ….), this paper chooses to use the $FEARS$ index developed by Da, Engelberg, and Gao (2015) to provide a new angle of music sentiment validation in the digital era and a linkage between a country's general investor mood and general investor sentiment. The $FEARS$ index is constructed

[9] https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker
[10] https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md#containment-and-closure-policies
[11] https://www.policyuncertainty.com/
[12] https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads

with 30 search terms[13] derived from words of economic sentiment in the Harvard and Lasswell dictionaries that has the largest negative correlation with the market. Then, for each search term, the daily Google Search Volume Index (SVI) of the corresponding word is retrieved[14] and their daily log differences are then computed (ΔSVI). Then for each time series, it would be winsorized at 5% level, regressed against weekday and month dummies, and standardized with mean 0 and unit variance to get the Adjusted Search Volume Index ($\Delta ASVI$). Then, the $FEARS$ index is calculated as $FEARS_{d,i} = \sum_{n=1}^{30} \Delta ASVI_{n,d,i}$ for search term n on day d for country i. Note that albeit the Da, Engelberg, and Gao (2015) paper only creates index for US only, yet later paper (Gao et al., 2020) demonstrated that the index could be extend to the context of other countries with language change in the chosen word. For this validation stage, only 16 countries[15] which use English as their first or second language and thus no change in the search terms were used. As shown in the 2015 paper, the FEARS index has a negative correlation with contemporaneous returns and then a reversal on the next day. If the $Music\ Sentiment$ positively reflects investor sentiments, then in the following panel regression: For country i on day d,

$$\begin{aligned} &Music\ Sentiment_{i,d} \\ &\quad = \alpha + \beta_1 FEARS_{i,d} + \beta_2 \Delta COVID_{i,d} + \beta_3 \Delta EPU_{i,d} + \beta_4 \Delta ADS_{i,d} + \varepsilon_{i,d} \end{aligned} \tag{2}$$

[13] The terms are: “Gold Prices”, “Recession”, “Gold Price”, “Depression”, “Great Depression”, “Gold”, “Economy”, “Price of gold”, “The Depression”, “Crisis”, “Frugal”, “GDP”, “Charity”, “Bankruptcy”, “Unemployment”, “Inflation rate”, “Bankrupt”, “The Great Depression”, “Car Donate”, “Capitalization”, “Expense”, “Donation”, “Savings”, “Social Security Card”, “The Crisis”, “Default”, “Benefits”, “Unemployed”, “Poverty”, “Social Security Office”

[14] Retrieved through the R package gtrendsR

[15] English-speaking countries included are 'AU', 'BE', 'CA', 'CH', 'DE', 'DK', 'GB', 'GR', 'MY', 'NL', 'NO', 'NZ', 'PH', 'SE', 'SG', 'US'

β_1 should be negative for $FEARS_d$ and positive for $FEARS_{d-1}$, which is exactly shown in Table 1. Both $FEARS_d$ and $FEARS_{d-1}$ are significant at 1% level.

$$Insert\ Table\ 1$$

To further consolidate our $Music\ Sentiment$, this paper tries to follow Edmans et al. (2021) paper and uses country-level MSCI index dollar return[16] ($\Delta MSCI$) as a measure of stock market performance, and regress against $Music\ Sentiment^u$, the residuals of the regression in equation (2) because all control factors in the equation are related to stock returns. Besides $Music\ Sentiment^u$, a series of $Controls$ i added: $\Delta ASWI$, the daily return of the MSCI World Index to account for the global stock market trend; and ΔVIX, the implied volatility of the $S\&P$ 500[17] (Da, Engelberg & Gao, 2015) which accounts for investors' expectations on the volatility of the U.S. stock market over the following 30 days. For $\Delta ASWI$, ΔVIX and $\Delta MSCI$, their lag values up to two days are included in the regressions to account for autocorrelations ($lags$). Henceforth, the regression of stock return against music sentiment and controls goes as follows: For country i on day d,

$$\Delta MSCI_{i,d} = \alpha + \beta_1 Music\ Sentiment_{i,d}^u + \sum\Gamma_1 \cdot Controls_{i,d} + \sum\Gamma_2 \cdot lags_{i,d} + \varepsilon_{i,d} \qquad (3)$$

$$Insert\ Table\ 2$$

[16] All MSCI data are retrieved from https://www.msci.com/end-of-day-data-search

[17] Retrieved from Yahoo Finance

Table 2 reports the regression results of equation (3). It is noteworthy that in column (1), the contemporaneous return and 1-day-lag return are summed and regressed against the summed $Music\ Sentiment$ of contemporaneous and 1-day-lag values. This treatment is used for accounting the non-synchronicity between the opening and closing time of the stock markets and Spotify statistics reporting time[18] across different countries. The result in Table 2 is consistent with the findings of Edmans et al. (2021) with $Music\ Sentiment^{u}_{d_{0,1}}$ being significant at 1% level and 1 standard deviation increase in $Music\ Sentiment^{u}_{d_{0,1}}$ is associated with 4.36% increase in return in the same period. For $Controls$, both $\Delta ASWI$ and ΔVIX are positively correlated with $\Delta MSCI$ and significant at 1% level.

3.3 Spotify Music Sentiment for Cryptocurrencies

With $Music\ Sentiment$ being well-established as shown in Section *2.1* and *2.2,* the results could be extended to sentiment in cryptocurrency market. As cryptocurrency trading data by country is extremely hard to get, a global scale sentiment index is needed to account for the holistic sentiment of the cryptocurrency market. As discovered by Liu and Tsyvinski (2021) and Liu et al. (2022), investors' attention has great predictability in cryptocurrencies' returns. In their empirical studies, they use SVI of the word "Bitcoin" as a measure of positive investors' attention in cryptocurrencies, which country-level data could be easily retrieved at high frequency unlike other effects that only global data are available. Henceforth, to obtain a global music sentiment index for the

[18] Spotify charts are based on UTC time zone

cryptocurrency market[19], the music sentiment of each country is weighted by the SVI[20] of the word "Bitcoin" such that

$$CryptVal_d = \sum_{i=1}^{47} Music\ Sentiment_{i,d} \cdot Google_{i,d} \qquad (4)$$

where $Google_{i,d}$ is the Google Trend search volume index of the word "Bitcoin" on day d in country i, and

$Music\ Sentiment_{i,d}$ is the result from equation $(1c)$

The cryptocurrency music sentiment index ($CryptVal$) is normalized to have a mean of 0 and unit variance.

3.4. Validating the Music Sentiment index for Cryptocurrency Market

There are few well-established academic sentimental measures for the investor sentiments in the cryptocurrency market. Therefore, this paper turns to industry-standard parameters and the Crypto Fear & Greed Index ($FearGreed$)[21] is chosen. The index is created by the CNNMoney and measures the "Fear" and "Greed" in the cryptocurrency market based on data of Bitcoin and other major cryptocurrencies. Its creation is based on the assumption that investors tend to get greedy

[19] Besides the music sentiment and investor attention parameters, an extra parameter of income, GDP per capita, was considered to account for country-level income effect. This measure is found to have neglectable effect to the overall result and thus excluded for simplicity.
[20] The daily Google Trend data used in this paper is scraped by using the R package gtrendsR (https://cran.r-project.org/web/packages/gtrendsR/gtrendsR.pdf) repeatedly with various IP address.
[21] https://alternative.me/crypto/fear-and-greed-index/

when the market is rising owing to Fear Of Missing Out (Greed), as well as sell their cryptocurrencies irrationally when there are negative returns (Fear). This assumption is aligned with various previous researches which state that momentum plays a big part in forecasting cryptocurrencies' return (Sockin & Xiong, 2020; Liu & Tsyvinski, 2021). The Crypto Fear and Greed Index uses 5 data sources to construct the index, including volatility, market momentum/volume, social media, market capital, and trends. Table 3 reports details of the data sources and their corresponding academic supports. The index ranges from 0 to 100 where 0 means "Extreme Fear", while 100 means "Extreme Greed". The documentation of the index commenced on 2018-02-01 and therefore our sample period for the cryptocurrency market would be 2018-02-01 to 2021-12-31.

$Insert\ Table$ 3

To validate $CryptVal$, besides using $FearGreed$, $\Delta COVID$, which is also weighted by $Google$ as in equation (4); as well as ΔADS, ΔVIX, and ΔEPU used in previous sentiment validation are added as controls. The regression is shown as follows: For day d,

$$CryptVal_d = \alpha + \beta_1 FearGreed_d + \beta_2 \Delta ADS_d + \beta_3 \Delta VIX_d + \beta_4 \Delta EPU_d + \varepsilon_d \qquad (5)$$

Table 4 reports the result of the regression in equation (5). In column (1), $FearGreed_d$ is regressed against $CryptVal_d$ while in column $(2-6)$, each independent variable is regressed against $CryptVal_d$. $FearGreed$ meausres are significant at 1% level and positively correlate with $CryptVal$ in both cases. The result supports our hypothesis that music sentiment captures mood-induced mispricing and encourages risk-taking[22]. The residuals of the regression with equation (5) are denoted as $CryptVal^u$.

3.5. Cryptocurrencies and their risk factors

All cryptocurrencies price data are retrieved from CoinGecko. CoinGecko is the world's largest independent cryptocurrency data aggregator with over 13,000 cryptoassets tracked across more than 600 exchanges worldwide. It provides data including opening and closing prices, trading volume, as well as market capital. The prices in CoinGecko for a cryptoasset is calculated using a global volume-weighted average price across all exchanges tracked while the volume is calculated as the total sum of all trading volume across exchanges.[23] CoinGecko lists both active and defunct cryptocurrencies and thus attenuating any survivorship bias. All cryptocurrencies with market capitalization over USD 1 million and have full dataset in the period of 2018-02-01 to 2021-12-31 are retrieved from CoinGecko which results in a sample size of 159 cryptocurrencies. All cryptocurrency's returns (Ret^e) in the following sections are excess returns calculated as the log difference of daily closing prices subtracted by daily risk-free return approximated by using the 1-month Treasury Securities market yield collected from FRED[24].

[22] Interestingly, $FearGreed$ is no longer significant if we change the scale to weekly.
[23] CoinGecko describing their pricing formula: https://www.coingecko.com/en/methodology#:~:text=The%20price%20of%20a%20cryptoasset,volume%2Dweighted%20average%20price%20formula.
[24] https://fred.stlouisfed.org/series/DGS1MO

For cryptocurrency risk factors, Liu and Tsyvinski (2021) have dedicated in finding common risk factors across cryptocurrencies, which are the network effect and investor attention effect[25]. Network effect describes the positive network externality generates by higher users' adoption rate while investor attention describes how investors allocate their scarce attention to vast amount of information in the market when making investment decisions (Peng & Xiong, 2006). This paper builds on their model and supports that $CryptVal$ offers additional explanatory and even predictive power in cryptocurrency returns. In their paper, Network effect (PC^{net}) is the first principal component of four primary measures, namely the daily change of the number of wallet users, the number of transaction count, the number of payment count, and the number of active addresses. All these data are available in Blockchain.info[26]. For investor attention effect, the paper distinguishes positive and negative attention and construct them by using SVI. For positive investor attention ($attn^{pos}$), the paper uses the difference between contemporaneous and previous four-week average SVI for the word "Bitcoin" as a proxy. For negative attention ($attn^{neg}$), the paper uses the ratio of the SVI of the phrase "Bitcoin Hack" and the SVI of the word "Bitcoin" as a proxy.

Other cryptocurrency price factors used are the cryptocurrency small-minus-big factor ($CSMB$), calculated as the daily difference between the combined return of the smallest 30% coins and the biggest 30% coins (Liu et al., 2022); and the log market capital ($MCAP^{log}$).

[25] Liu et al. (2022) has also established a 3-factor common risk model that resembles the Fama-French 3 factor model. Yet, that model is rather hard to interpret and thus the model of network and investor attention effects is chosen.

[26] https://www.blockchain.com/charts#network

4. Results

4.1. Excess Return

This paper, for main result, investigates the correlation between music sentiment and cryptocurrency's returns. The following baseline panel regression is estimated:

$$Ret_{i,d}^{e} = \alpha + \beta_1 CryptVal_{i,d}^{u} + \beta_2 \mathrm{PC}_{i,d}^{\mathrm{net}} + \beta_3 \mathrm{attn}_{i,d}^{\mathrm{pos}} + \beta_4 \mathrm{attn}_{i,d}^{\mathrm{neg}} + Ret_{i,d-1}^{e} + \varepsilon_{i,d} \tag{6}$$

for cryptocurrency i in day d.

All the variables are explained in *Section 2.5.* and the 1-day-lag value of crypto's returns is controlled to account for autocorrelation. $CryptVal^{u}$, instead of $CryptVal$ is used because all the controls in equation (5) reflect macroeconomic and general cryptocurrency market environment which are related to cryptocurrency's returns[27]. Table 5 demonstrates the results of the regression for equation (6).

$Insert\ Table\ 5$

Note that in column (1), the dependent variable is $Ret_{d_0+d_1}^{e}$ represents the combined return of day 0 and 1 returns. This treatment is used to account for the non-synchronicity between different time zone in different countries and a uniform cryptocurrency market. From the table, we can see that music sentiment is significantly and positively correlated with cryptocurrency's returns for day 0

[27] Liu and Tsyvinski (2021) has also mentioned potential seasonal effect of cryptocurrencies (e.g. lower returns in Saturdays and Sundays) but as we have regressed on months and weekdays during the construction of $Music\ Sentiment$, seasonal dummies are not included.

and 1, then reverse in day 2 and 3 before losing explanatory power. The process of sentiment-induced mispricing is reflected by music sentiment in the first two days before the market returns to a more efficient state in the latter two days. In day 0 and 1, one standard deviation in $CryptVal^u$ leads to 1.41bps (103% annualized) increase in cryptocurrency's excess returns.

Turning to control variables, interestingly, albeit significant, most of their signs are counterintuitive, most likely because of the combined effect of the variables. Hence, a robustness check, which Ret^e is regressed against each control variable, is performed to check if the control variables behave intuitively. Table 6 presents the result of the robustness check that all control variables are significant on their own with the expected signs.

$Inset\ Table\ 6$

Throughout this paper, a lot of weighting (e.g. using SVI of the word "Bitcoin" when creating $CryptVal$) and validation methods (e.g. use of $FearGreed$) are related to the cryptocurrency Bitcoin. It is conceivable that if one wonders whether the results in this paper can represent the entire market or only Bitcoin. Hence, another robustness check where the regression in equation (6) is run with Bitcoin removed from the sample size is performed and its result is reported in Table 7. It can be seen that the result is largely the same as of that in Table 5 with $CryptVal^u$ remaining to be positively and significantly correlated with cryptocurrency returns and displays a pattern that resembles sentiment-induced mispricing.

$Insert\ Table\ 7$

4.2.Volatility

As described in De Long et al. (1990), irrational noise trader affected by pseudosignals (e.g. sentiment) pushes market price away from efficient price. The more extreme the sentiment is, regardless of direction, the further the market price is away from the efficient price. As market will eventually correct itself, this process in other words, pushes up volatility. With this being said, it is interesting to further investigate the relationship between volatility of cryptocurrencies and music sentiment:

$$Vol_{i,d} = \alpha + \beta_1|CryptVal_{i,d}| + \sum\Gamma_1 Controls_{i,d} + \sum\Gamma_2 lags_{i,d} + \varepsilon_{i,d} \tag{7}$$

where $Vol_{i,d}$ is the rolling standard deviation in cryptocurrency's return for the past 30 days,

$lags_{i,d}$ includes one-day-lag value of both $Vol_{i,d}$ and $Ret^{e}_{i,d}$, and

$Controls_{i,d}$ includes $PCnet$, $attn^{pos}$, $attn^{neg}$, and $FearGreed$

for cryptocurrency i on day d

Note that the absolute value of music sentiment is used in this case as only the magnitude of the sentiment is important. Table 8 presents the result of the regression.

$Insert\ Table\ 8$

From Table 8, a strong and significant correlation between music sentiment and cryptocurrency market volatility is documented, one standard deviation increase in absolute $CryptVal$ leads to a 0.036bps increase in daily contemporaneous cryptocurrency market volatility. This further strengthens the hypothesis of music sentiment reflecting the sentimental-induced mispricing in the cryptocurrency market. It is also interesting to find a significant positive correlation between investor attentions and volatility, regardless on positive or negative, which suggest attention-driven overreaction-momentum in recent theories (Sockin & Xiong, 2020). The slightly negative coefficient in $FearGreed$ may be due to the overall trend of higher volatility in bearish market (Liu et al., 2022). All the results remain similar with no significant change even after Bitcoin is removed from the sample.

4.3. Exposure to music sentiment-induced mispricing

After establishing evidence about how music sentiment acts as a reflection of sentiment-induced mispricing, this paper further explore what kinds of cryptocurrencies are more exposed to sentiment-induced mispricing.

4.3.1. Size

To evaluate the impact of sentiment towards cryptocurrencies with different sizes, the sample universe of cryptocurrencies is sorted into quintiles according to their mean market capitalization throughout the sample period (bucket 1 as cryptocurrencies with the smallest market capitalization and bucket 5 are those with the biggest). Then, for each bucket, a regression same as equation (6) is run. The results are reported in Table 9 shows an almost monotonic increase in $CryptVal^u$ coefficient from bucket 2 to 5 and all 4 coefficients are significant at 1% level. In other words, the larger coins are more exposed to music sentiment-induced mispricing. This finding, albeit is opposite of what previous researches in stock market shown (Baker & Wurgler, 2006; Edmans et al., 2007), make sense in the cryptocurrency market as it aligns with the findings in the empirical studies of Peng & Xiong (2006) and Andrei & Halser (2015) which show that bigger and more well-known assets receive more investor attention, and thus are more easily subjected to overreaction. In fact, coins with the smallest market capitalization probably receive little to no attention, $CryptVal^u$is not significant at all and even displays negative coefficient.

$Insert\ Table$ 9

Similar result can also be discovered when testing the sensitivity of $CryptVal^u$ coefficients. For each coin, a simple OLS regression similar to equation (6) and all the $CryptVal^u$ coefficients, which reflects the exposure of music sentiment for each coin, are collected. It is found that the correlation between the music sentiment betas and average coin market capitalization is 0.31 (as shown in Table 10), reinforcing the positive correlation between coin size and attention, and exposure to sentiment effect.

4.3.2. Illiquidity

As suggested by Baker & Stein (2004), liquidity increases with sentiment as under the assumption of the existence of short-sale ban, irrational traders can only act if they have bullish views (high sentiment) in some stocks and the flock of irrational traders increase liquidity for those stocks. However, it is possible to short coins through Contracts for difference (CFDs), margin trading platforms (e.g. Kraken, Binance) or options trading etc.[28] and thus this argument may not hold in the cryptocurrency market. Henceforth, this paper tries to present another story for the relationship between liquidity and sentiment: retail cryptocurrency traders are not familiar with shorting and hence only act when they have a bullish view in a certain coin. CNBC has reported that more than

[28] https://www.investopedia.com/news/short-bitcoin/

1/3 of crypto investors have little to no knowledge in cryptocurrencies [29] and shorting cryptocurrency is much less straightforward than simply buying it. It is probable that retail crypto traders do not take advantage of shorting is because of inadequate knowledge in its method. Although it is hard to test the actual reason for investors to not engage in short-selling, a series of validation is conducted to support the hypothesis. Firstly, the sensitivity of sentiment in coins of different liquidity is tested. The sample cryptocurrencies are first sorted into quintiles (group 1 as the most liquid coins and group 5 as the most illiquid coins) according to Amihud Illiquidity Measure (Amihud, 2002) ($Illiq$). Then for each group, the coins' returns are estimated by using the following equation:

$$Ret^{e}_{i,d} = \alpha + \beta_1 CryptVal^{u}_{i,d} + \sum\Gamma_1 Controls_{i,d} + \beta_2 CSMB + \beta_3 MCAP^{log} + \varepsilon_{i,d} \quad (8)$$

for cryptocurrency i in day d.

The $Controls$ used here are the same as equation (6), namely $\mathrm{PC}^{\mathrm{net}}_{i,d}$, $\beta_3 \mathrm{attn}^{\mathrm{pos}}_{i,d}$, $\beta_4 \mathrm{attn}^{\mathrm{neg}}_{i,d}$, and $Ret^{e}_{i,d-1}$. According to Liu et al. (2022), size premium ($CSMB$) is more pronounced for coins with higher arbitrage cost, size premium and log market capitalization ($MCAP^{log}$) is added in the controls. Table 11 reports the result of this estimation.

$Insert\ Table$ 11

[29] https://www.cnbc.com/2021/03/04/survey-finds-one-third-of-crypto-buyers-dont-know-what-theyre-doing.html

As expected, $CSMB$ becomes more significant and positive for more illiquid groups. It is also found that $CryptVal^u$ is only significant when explaining the returns of the more liquid coins (group 1-3)[30]. This gives an initial prove of the aforementioned assumption. To give further proof, this paper tries to examine the relationship of cryptocurrencies and music sentiment under different sentiment environment. Firstly, the sample time period is sorted into positive sentiment period (positive $CryptVal$) and negative sentiment period (negative $CryptVal$). Then, equation (6) and (7) are used to estimate the return and volatility under different sentiment period. Table 12 reports the results.

$$Insert\ Table\ 12$$

It can be seen that for both return and volatility, magnitude of the sentiment betas is higher for positive sentiment. This observation still holds when they are weighted by the standard deviation of return/volatility. The reduction in sentiment beta when regressing against volatility under negative sentiment can be seen as a reduction in noise traders during bearish environment, and the reduction in sentiment beta when regressing against returns suggests that there are fewer extreme speculations in bearish environment, giving more validity to the aforementioned assumption.

5. Conclusion

[30] Similar results can a be found when Amihud Illiquidity measure is changed to the illiquid measure developed by Kyle and Obizhaeva (2016).

This paper sheds light on explores the mood-induced mispricing phenomenon in the cryptocurrency market by using music sentiment data. Notwithstanding the phenomenon is a well-documented phenomenon in traditional equity market, it has not been adequately explored unstudied in the novel cryptocurrency market. This paper documents a significant and positive relationship between music sentiment and contemporaneous cryptocurrency market returns after controlling for network effect, investor attention effects, general fear and greed in the cryptocurrency market, as well as autocorrelation. A significant reversal is also discovered in the following two days after the initial shock. All in all, these results are consistent with previous studies in temporary sentiment-induced mispricing.

Furthermore, this paper shows a positive and significant relationship between absolute music sentiment and cryptocurrency market volatility, which is consistent with previous researches in noise traders. It is also found that music sentiment effect is more pronounced for large and liquid cryptocurrencies. Overall, this paper presents solid evidence that investor's mood does significantly affect the cryptocurrency market.

References

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31-56. https://doi.org/10.1016/s1386-4181(01)00024-6

Andrei, D., & Hasler, M. (2015). Investor attention and stock market volatility. *Review of Financial Studies*, *28*(1), 33-72. https://doi.org/10.1093/rfs/hhu059

Aruoba, S. B., Diebold, F. X., & Scotti, C. (2009). Real-Time Measurement of Business Conditions. *Journal of Business & Economic Statistics*, *27*(4), 417-427. https://doi.org/10.1198/jbes.2009.07205

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, *7*(3), 271-299. https://doi.org/10.1016/j.finmar.2003.11.005

BAKER, M., & WURGLER, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645-1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., & Menkveld, A. J. (2018). Equilibrium bitcoin pricing. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3261063

Brusa, F., Savor, P., & Wilson, M. (2020). One Central Bank to Rule Them All. *Review of Finance*, *24*(2), 263-364. https://doi.org/10.1093/rof/rfz015

Chen, C. Y., Despres, R., Guo, L., & Renault, T. (2019). What makes cryptocurrencies special? Investor sentiment and return predictability during the bubble. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3398423

Clore, G. L., Schwarz, N., & Conway, M. (1994). Affective causes and consequences of social information processing. In *Handbook of social cognition: Basic processes; Applications* (pp. 323-417). Lawrence Erlbaum Associates, Inc.

Cong, L. W., Li, Y., & Wang, N. (2020). Tokenomics: Dynamic adoption and valuation. https://doi.org/10.3386/w27222

Da, Z., Engelberg, J., & Gao, P. (2015). The Sum of All FEARS Investor Sentiment and Asset Prices. *The Review of Financial Studies*, *28*(1), 1-32. https://doi.org/10.1093/rfs/hhu072

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703-738. https://doi.org/10.1086/261703

Edmans, A., Fernandez-Perez, A., Garel, A., & Indriawan, I. (2021). Music sentiment and stock returns around the world. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3776071

EDMANS, A., GARCÍA, D., & NORLI, Ø. (2007). Sports sentiment and stock returns. *The Journal of Finance*, *62*(4), 1967-1998. https://doi.org/10.1111/j.1540-6261.2007.01262.x

Fishbein, M. (1963). An investigation of the relationships between beliefs about an object and the attitude toward that object. *Human Relations*, *16*(3), 233-239. https://doi.org/10.1177/001872676301600302

Gao, Z., Ren, H., & Zhang, B. (2020). Googling Investor Sentiment around the World. *Journal of Financial and Quantitative Analysis*, *55*(2), 549-580. https://doi.org/10.1017/S0022109019000061

Hirshleifer, D., Jiang, D., & DiGiovanni, Y. M. (2020). Mood beta and seasonalities in stock returns. *Journal of Financial Economics*, *137*(1), 272-295. https://doi.org/10.1016/j.jfineco.2020.02.003

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, *58*(3), 1009-1032. https://doi.org/10.1111/1540-6261.00556

Kyle, A. S., & Obizhaeva, A. A. (2016). Market microstructure invariance: Empirical hypotheses. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2722524

Liu, Y., & Tsyvinski, A. (2021). Risks and Returns of Cryptocurrency. *The Review of Financial Studies*, *34*(6), 2689-2727. https://doi.org/10.1093/rfs/hhaa113

Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, *77*(2), 1133-1177. https://doi.org/10.1111/jofi.13119

Mehr, S. A., Knox, M., Ketter, D., Pickens-Jones, D. M., Atwood D., & ... (2019). Universality and diversity in human song. *Science*, *366*. https://doi.org/10.1126/science.aax0868

Nasekin, S., & Chen, C. Y. (2020). Deep learning-based cryptocurrency sentiment construction. *Digital Finance*, *2*(1-2), 39-67. https://doi.org/10.1007/s42521-020-00018-y

North, A. C., & Hargreaves, D. J. (1996). Situational influences on reported musical preference. *Psychomusicology: A Journal of Research in Music Cognition*, *15*(1-2), 30-45. https://doi.org/10.1037/h0094081

Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), 563-602. https://doi.org/10.1016/j.jfineco.2005.05.003

Sellier, A. L., Scopelliti, I., & Morewedge, C. K. (2020). Corrigendum: Debiasing training improves decision making in the Field. *Psychological Science*, *31*(6), 762-762. https://doi.org/10.1177/0956797620930211

Sockin, M., & Xiong, W. (2020). A model of cryptocurrencies. https://doi.org/10.3386/w26816

Terry, P. C., Parsons-Smith, R. L., & Terry, V. R. (2020). Mood responses associated with COVID-19 restrictions. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.589598

Wiggins, R. (2015). Weather-induced mood, institutional investors, and stock returns. *CFA Digest*, *45*(7). https://doi.org/10.2469/dig.v45.n7.14

Appendix. Variable Definitions

Variables	Definition
$FEARS$	An index that reflects country-level market sentiment. It is constructed as the sum of the winsorized and standardized log difference of 30 economic terms' Google Search Volume Index (SVI) chosen in Da, Engelberg, and Gao (2015).
$\Delta COVID$	The first difference of the stringency index of government restrictions in response to COVID-19 taken from the University of Oxford's COVID-19 government response index. (Source: https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker)
ΔEPU	The first difference of the U.S. Economic Policy Uncertainty Index. (Source: https://www.policyuncertainty.com/)
ΔADS	The first difference of the U.S. Aruoba, Diebold, and Scotti Index. (Source: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads)
$Music\ Sentiment$	Residuals of the aggregated stream-weighted average valence of the daily top-200 songs after being regressed against weekday and months dummies.
$Music\ Sentiment^u$	The residuals of $Music\ Sentiment$ regressing against $FEARS$,$\Delta COVID$,ΔEPU, and ΔADS.
ΔVIX	Percentage change of the implied volatility of the S&P 500. (Source: https://finance.yahoo.com/quote/%5EVIX/)
$\Delta ASWI$	Return of the MSCI World Index. (Source: https://www.msci.com/end-of-day-data-search)
$\Delta MSCI$	Return of the country-level MSCI stock Index. (Source: https://www.msci.com/end-of-day-data-search)
$FearGreed$	Crypto Fear & Greed Index (Source: https://alternative.me/crypto/fear-and-greed-index/)
PC^{net}	First principal component of four primary measures, namely the daily change of the number of wallet users, the number of transaction count, the number of payment count, and the number of active addresses. (Source: https://www.blockchain.com/charts#wallet)
$attn^{pos}$	Deviation between contemporaneous SVI for the word "Bitcoin" and its four-week average.
$attn^{neg}$	Ratio between the SVI of the word "Bitcoin Hack" and "Bitcoin".
Ret^e	Excess return of a cryptocurrency (Source: https://www.coingecko.com/)
$CryptVal$	Weighted sum of country-level $Muisc\ Sentiment$ weighted by the SVI of the word "Bitcoin".
$CryptVal^u$	Residuals of $CryptVal$ regressing against $FearGreed, \Delta COVID, \Delta EPU, \Delta ADS$, and ΔVIX.

Vol	30-day rolling standard deviation of each cryptocurrency's excess return.
$MCAP$	Average market capitalization of each cryptocurrency across sample period.
PRC	Average price of each cryptocurrency across sample period.
$Illiq$	Amihud Illiquidity measure of each cryptocurrency
$Volume$	Average volume of each cryptocurrency across sample period.
$CSMB$	Size premium in the cryptocurrency market calculated as the difference between the combined return of the smallest 30% coin and largest 30% coins

Table 1: Validation of music-based sentiment measures

This table reports the relation between $Music\ Sentiment$ and contemporaneous $FEARS$ index and 1-day-lag $FEARS$ between the period January 1, 2017 to January 19, 2022. The panel OLS here is $Music\ Sentiment_{i,d} = \alpha + \beta_1 FEARS_{i,d} + \beta_2 \Delta COVID_{i,d} + \beta_3 \Delta EPU_{i,d} + \beta_4 \Delta ADS_{i,d} + \varepsilon_{i,d}$ The dependent variable $Music\ Sentiment$, is the residuals of daily change in the stream-weighted average valence of the top-200 songs played on Spotify for a country regressed against weekday and month dummies. For the independent variables, $FEARS_d$ represents the sentiment index constructed with Google Search Volume Index as in Da, Engelberg, and Gao (2015) while $FEARS_{d-1}$ is the $FEARS$ index with one day lag. $\Delta COVID$ is the daily change of the Containment and health index from OxCGRT. ΔEPU and ΔADS are the daily change of the US Economic Policy Uncertainty Index and US Aruoba, Diebold, and Scotti index. Both regressions include country fixed effects.

Constants are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. All coefficients are multiplied by 100.

Dependent Variable	$Music\ Sentiment_d$	
	(1)	(2)
$FEARS_d$	-0.54***	
	(-3.32)	
$FEARS_{d-1}$		0.35**
		(2.34)
$\Delta COVID_d$	-0.11	-0.11
	(-0.70)	(-0.66)
ΔEPU_d	0.078***	0.079***
	(2.68)	(2.72
ΔADS_d	0.10	0.12
	(0.09)	(0.11)
Fixed Effects	Countries	Countries
R^2	0.0014	0.0009
$Obs.$	14,467	14,467

Table 2: Music Sentiment and daily stock market return

This table reports the relation between contemporaneous to 4-day-lead daily stock market returns from January 1, 2017 to January 19, 2022. The panel regression used is $\Delta MSCI_{i,d} = \alpha + \beta_1 Music\ Sentiment^u_{i,d} + \sum\Gamma_1 \cdot Controls_{i,d} + \sum\Gamma_2 \cdot lags_{i,d} + \varepsilon_{i,d}$. The dependent variable $\Delta MSCI$ is the daily return of the country-level $MSCI$ index. For independent variables, $Music\ Sentiment^u$ is the residuals of the regression in Table 1 column (1). For the $Controls$, ΔASWI is the daily return of the MSCI World Index and ΔVIX, the implied volatility of the S&P 500. For ΔASWI, ΔVIX and ΔMSCI, their lag values up to two days are also included in the regressions to account for autocorrelations ($lags$). Note that $Music\ Sentiment^u_{d_{0,1}}$ and $MSCI_{d_{0,1}}$ refer to the sum of contemporaneous and 1-day-lag values.

Constants and lags are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variables	$\Delta MCSI_{d_{0,1}}$	$\Delta MCSI_{d+1}$	$\Delta MSCI_{d+2}$	$\Delta MSCI_{d+3}$	$\Delta MSCI_{d+4}$
	(1)	(2)	(3)	(4)	(5)
$Music\ Sentiment^u_{d_{0,1}}$	0.15***				
	(8.55)				
$Music\ Sentiment^u_d$		0.12*	-0.23*	-0.08***	-0.05
		(1.88)	(-1.85)	(-2.60)	(-1.25)
ΔVIX	1.96***	-5.95***	3.09***	-0.15	0.64
	(4.33)	(-9.55)	(3.91)	(-0.25)	(1.58)
$\Delta ASWI$	214.7***	-191***	51.5**	-23.6	37.2***
	(10.9)	(-6.23)	(2.13)	(-1.56)	(2.85)
Fixed Effects	Countries	Countries	Countries	Countries	Countries
R^2	0.5528	0.5637	0.1405	0.0497	0.0457
$Obs.$	5,052	5,052	5,052	5,052	5,052

Table 3: Data Sources of the Crypto Fear & Greed Index

Table 3 summarizes the data sources and their corresponding weightings on the Crypto Fear & Greed Index according to its documentation.

Data Sources	**Weightings**	**Description**
Volatility	25%	Comparing the current volatility and max. drawdowns of bitcoin and compare it with the corresponding average values of the last 30 days and 90 days. An unusual rise in volatility is argued as a sign of a fearful market, which aligns with the result of Liu et al. (2022) that documented negative correlations between volatility and returns.
Market Momentum	25%	Comparing the current market momentum with their 30 and 90 days lag values. High momentum is argued as evidence as signs of overly bullish market, which aligns with the result of Liu & Tsyvinski (2021) which documented positive correlations between market momentum and returns.
Social Media	15%	Twitter posts and hashtags interactions related to major cryptocurrencies are documented. A high interaction rate is argued as a bullish market behaviour, which is also documented in Liu & Tsyvinski (2021) paper as a proxy of investor attention.
Dominance	10%	It is argued that a rise in return of cryptocurrencies with higher market capital (safe haven) is due to the lack of confidence in smaller alt-coins. This argument, to a certain extent, is supported by Liu et al. (2022) paper which showed that size premium is more pronounced when cost of arbitrage (e.g. implied volatility) is higher.
Trends	10%	Google Search Volume Index of cryptocurrencies and their related queries are used to evaluate trends, which aligns with how Liu & Tsyvinski (2021) measured positive and negative investors' attentions.
Survey	15%	Paused in sample period

Table 4: Validating the music sentiment measure in cryptocurrency market

This table reports the relation between music sentiment and Crypto Fear & Greed index from January 1, 2017 to December 31, 2021. The simple OLS used is $CryptVal_d = \alpha + \beta_1 FearGreed_d + \beta_2 \Delta ADS_d + \beta_3 \Delta VIX_d + \beta_4 \Delta EPU_d + \varepsilon_d$. The dependent variable $CryptVal$ is the daily weighted average of $Music\ Sentiemnt$ weighted by Google Search Volume Index of the word "Bitcoin", same weighted average method is applied in $\Delta COVID$. For ΔEPU, ΔADS and ΔVIX, they are constructed totally the same as that in Table 1 and 2 with only U.S. values. For $FearGreed$, it is an industry-standard index that measure the sentiment (fear/greed) in the cryptocurrency market. All coefficients are multiplied by 100.

Constants are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variable	$CryptVal_d$					
	(1)	(2)	(3)	(4)	(5)	(6)
$FearGreed_d$	0.39***	0.39***				
	(0.01)	(3.39)				
$\Delta COVID$	-0.05		-0.04			
	(0.01)		(-0.34)			
ΔEPU	0.04			0.04		
	(0.00)			(1.32)		
ΔADS	-3.23				-2.34	
	(1.01)				(-0.286)	
ΔVIX	-30.9*					-31.3*
	(2.00)					(-1.936)
Fixed Effects	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies
R^2	0.028	0.021	0.000	0.002	0.000	0.004
$Obs.$	765	765	765	765	765	765

Table 5: Music Sentiment and daily cryptocurrency market return

This table reports the relation between cryptocurrency return and music sentiment in the period February 1, 2018 to December 31, 2022. The panel regression used is $Ret_{i,d}^{e} = \alpha + \beta_1 CryptVal_{i,d}^{u} + \beta_2 \mathrm{PC}_{i,d}^{\mathrm{net}} + \beta_3 \mathrm{attn}_{i,d}^{\mathrm{pos}} + \beta_4 \mathrm{attn}_{i,d}^{\mathrm{neg}} + Ret_{i,d-1}^{e} + \varepsilon_{i,d}$. The dependent variable Ret_{d}^{e} is the contemporaneous cryptocurrency excess returns and $Ret_{d_0+d_1}^{e}$ is the combined return of day 0 and 1. For independent variables, $CryptVal_{d_0}^{u}$ is the residual of the regression in Table 4 columns (1) which represents music sentiment index controlled for macroeconomic environment and $FearGreed$ index. PC^{net} is an approximation of cryptocurrency network effect; $attn^{pos}$ is a proxy for positive investor attention, and $attn^{neg}$ is a proxy for negative investor attention. 1-day-lag return of the cryptocurrency excess return is also controlled.

Constants are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variable	$Ret_{d_0+d_1}^{e}$(%)	Ret_{d+1}^{e}(%)	Ret_{d+2}^{e}(%)	Ret_{d+3}^{e}(%)	Ret_{d+4}^{e}(%)
	(1)	(2)	(3)	(4)	(5)
$CryptVal_{d_0}^{u}$	0.024***	0.022***	-0.021***	-0.012***	-0.004
	(6.65)	(8.0089)	(-7.70)	(-4.37)	(-1.34)
$PC_{d_0}^{net}$	-0.002	-0.006***	0.005***	-0.001	-0.026***
	(-0.86)	(-3.40)	(2.98)	(-0.50)	(-14.8)
$attn_{d_0}^{pos}$	0.003***	0.001***	0.001***	0.001***	0.000
	(11.76)	(8.21)	(7.13)	(6.00)	(0.13)
$attn_{d_0}^{neg}$	0.044***	0.023***	0.011**	0.033***	-0.025***
	(6.93)	(3.87)	(2.36)	(7.1163)	(-5.27)
Ret_{d-1}^{e}(%)	-0.934***	-0.027***	0.008	-0.005	-0.005
	(-8.25)	(-3.05)	(0.87)	(-0.55)	(-0.58)
Fixed Effects	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies
R^2	0.0065	0.0021	0.0013	0.0008	0.0023
$Obs.$	109,074	109,074	109,074	109,074	109,074

Table 6: Robustness check on the control variables in Table 5

This table tests the authenticity of each control variables in equation (5) $Ret^e_{i,d} = \alpha + \beta_1 CryptVal^u_{i,d} + \beta_2 \mathrm{PC}^{\mathrm{net}}_{i,d} + \beta_3 \mathrm{attn}^{\mathrm{pos}}_{i,d} + \beta_4 \mathrm{attn}^{\mathrm{neg}}_{i,d} + Ret^e_{i,d-1} + \varepsilon_{i,d}$. $Ret^e_{d_0+d_1}$ is regressed against each of the independent variable in Table 5, namely PC^{net}, $attn^{pos}$,$attn^{neg}$, and $CryptVal^u$.

Constants are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variable	$Ret^e_{d_0+d_1}$(%)	$Ret^e_{d_0+d_1}$(%)	$Ret^e_{d_0+d_1}$(%)	$Ret^e_{d_0+d_1}$(%)	$Ret^e_{d_0+d_1}$(%)
	(1)	(2)	(3)	(4)	(5)
$PCnet$	0.01***				-0.003
	(7.73)				(-1.14)
$attn^{pos}$		0.002***			0.002***
		(17.34)			(11.10)
$attn^{neg}$			-0.04***		0.04***
			(-11.07)		(6.65)
$CryptVal^u_t$				0.03***	0.02***
				(10.196)	(6.69)
Fixed Effects	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies
R^2	0.0003	0.0013	0.0005	0.0008	0.0018
$Obs.$	209,402	236,592	241,044	126,246	109,074

Table 7: Robustness Check with Bitcoin removed

This table reports the relation between cryptocurrency market return with Bitcoin removed with music sentiment. All the variables used in this table is same as that in Table 5.

Constants are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variables	$Ret^e_{d_0+d_1}$(%)	Ret^e_{d+1}(%)	Ret^e_{d+2}(%)	Ret^e_{d+3}(%)	Ret^e_{d+4}(%)
	(1)	(2)	(3)	(4)	(5)
$CryptVal^u_{i,d_0}$	0.024***	0.022***	-0.021***	-0.012***	-0.004
	(6.65)	(8.01)	(-7.70)	(-4.37)	(-1.34)
$PC^{net}_{d_0}$	-0.002	-0.006***	0.005***	-0.001	-0.026***
	(-0.86)	(-3.40)	(2.98)	(-0.50)	(-14.8)
$attn^{pos}_{d_0}$	0.003***	0.001***	0.001***	0.001***	0.000
	(11.8)	(8.21)	(7.13)	(6.00)	(0.13)
$attn^{neg}_{d_0}$	0.044***	0.018***	0.011**	0.033***	-0.025***
	(6.93)	(3.87)	(2.36)	(7.12)	(-5.27)
Ret^e_{d-1}(%)	-0.094***	-0.027***	0.077	-0.005	-0.005
	(-8.25)	(-3.05)	(0.87)	(-0.55)	(-0.58)
Fixed Effects	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies
R^2	0.0065	0.0021	0.0013	0.0008	0.0023
$Obs.$	109,074	109,074	109,074	109,074	109,074

Table 8: Music Sentiment and Cryptocurrency's volatility

This table reports relation between the volatility of cryptocurrency return and music sentiment from February 1, 2018 to December 31, 2021. The panel regression used is $Vol_{i,d} = \alpha + \beta_1|CryptVal_{i,d}| + \sum\Gamma_1 Controls_{i,d} + \sum\Gamma_2 lags_{i,d} + \varepsilon_{i,d}$. The dependent variable Vol represents the rolling standard deviation of cryptocurrency's excess returns of the past 30 days. For independent variables, $|CryptVal|$ is the absolute value of music sentiment derived from equation (4). PC^{net} is an approximation of cryptocurrency network effect; $attn^{pos}$ is a proxy for positive investor attention, and $attn^{neg}$ is a proxy for negative investor attention. For $FearGreed$, it is an industry-standard index that measure the sentiment (fear/greed) in the cryptocurrency market. In the regression in column (2), the one-day-lag value of cryptocurrency excess return and Vol are also controlled yet not reported. All coefficients are multiplied by 10,000.

Constants and lags are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variable	Vol	
	(1)	(2)
$\|CryptVal\|$	0.052***	0.060***
	(8.29)	(9.11)
$PCnet$		0.017***
		(3.65)
$attn^{pos}$		0.009***
		(19.2)
$attn^{neg}$		0.119***
		(9.00)
$FearGreed$		-0.002***
		(-9.55)
Fixed Effects	Cryptocurrencies	Cryptocurrencies
R^2	0.0003	0.0036
$Obs.$	252,969	221,328

Table 9: Music Sentiment and daily cryptocurrency market returns sort by market capitalization

This table reports the different relations between cryptocurrency return of different size with music sentiment from February 1, 2018 to December 31, 2021. The panel regression used is $Ret_{i,d}^{e} = \alpha + \beta_1 CryptVal_{i,d}^{u} + \beta_2 \mathrm{PC}_{i,d}^{\mathrm{net}} + \beta_3 \mathrm{attn}_{i,d}^{\mathrm{pos}} + \beta_4 \mathrm{attn}_{i,d}^{\mathrm{neg}} + Ret_{i,d-1}^{e} + \varepsilon_{i,d}$. The dependent variable $Ret_{d_0+d_1}^{e}$ is the combined cryptocurrency excess return of day 0 and 1. Among the 159 sample cryptocurrencies, they are sorted by average market capitalization into quintile which columns (5) represents coins that have the largest market capitalization while column (1) are those which has the smallest. For independent variables, $CryptVal_{d_0}^{u}$ is the residual of the regression in equation (5) which represents music sentiment index controlled for macroeconomic environment and $FearGreed$ index. PC^{net} is an approximation of cryptocurrency network effect; $attn^{pos}$ is a proxy for positive investor attention, and $attn^{neg}$ is a proxy for negative investor attention. 1-day-lag return of the cryptocurrency excess return is also controlled.

Constants are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variable	$Ret_{d_0+d_1}^{e}$(%)				
	(1)	(2)	(3)	(4)	(5)
$CryptVal_{d_0}^{u}$	-0.003	0.022***	0.032***	0.036***	0.035***
	(-7.49)	(3.14)	(5.18)	(5.75)	(4.038)
$PC_{d_0}^{net}$	-0.014*	-0.002	0.008*	0.002	-0.006
	(-1.84)	(-0.44)	(1.94)	(0.56)	(-1.16)
$attn_{d_0}^{pos}$	0.004***	0.002***	0.003***	0.002***	0.002***
	(5.23)	(5.23)	(7.36)	(6.28)	(3.27)
$attn_{d_0}^{neg}$	0.081***	0.029**	0.028**	0.025**	0.055***
	(4.11)	(2.39)	(2.50)	(2.29)	(3.64)
Ret_{d-1}^{e}(%)	-0.146***	-0.029***	-0.028***	-0.052***	-0.098***
	(-7.49)	(-2.90)	(-2.87)	(-4.14)	(-2.77)
Fixed Effects	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies
R^2	0.014	0.022	0.004	0.005	0.007
$Obs.$	21,266	21,952	21,952	21,952	21,952

<u>Table 10: Correlation of music sentiment sensitivity with different fundamental factors</u>

This table reports the correlation of music sentiment sensitivity with different fundamental factors. For each cryptocurrency, a time series regression of $Ret_d^e = \alpha + \beta_1 CryptVal_d^u + \beta_2 \mathrm{PC}_d^{\mathrm{net}} + \beta_3 \mathrm{attn}_d^{\mathrm{pos}} + \beta_4 \mathrm{attn}_d^{\mathrm{neg}} + Ret_{d-1}^e + \varepsilon_{i,d}$ is run and the $\beta_1$is retrieved. Then, the correlation between $beta_1$ and fundamental factors (average across the entire sample period for each coin) of all coins is calculated. $MCAP$ refers to the average market capitalization, $Illiq$ refers to the Amihud Illiquidity measure, PRC refers to the average price, and $Volume$ refers to the average trading volume.

Fundamental Factors	Correlation with $CryptVal^u$ β
$MCAP$	0.31
$Illiq$	-0.09
PRC	0.016
$Volume$	-0.015

Table 11: Music Sentiment and daily cryptocurrency market returns sorted by Amihud Illiquidity measure

This table reports the different relations between cryptocurrency return of different liquidity with music sentiment from February 1, 2018 to December 31, 2021. The panel regression used is $Ret^{e}_{i,d} = \alpha + \beta_1 CryptVal^{u}_{i,d} + \sum\Gamma_1 Controls_{i,d} + \beta_2 CSMB + \beta_3 MCAP^{log} + \varepsilon_{i,d}$. The dependent variable $Ret^{e}_{d_0+d_1}$ is the combined cryptocurrency excess return of day 0 and 1. Among the 159 sample cryptocurrencies, they are sorted by Amihud Illiquidity measure into quintile which columns (5) represents coins that are the most illiquid while column (1) are those that are the most liquid. For the main independent variable, $CryptVal^{u}_{d_0}$ is the residual of the regression in equation (5) which represents music sentiment index controlled for macroeconomic environment and $FearGreed$ index. For $Controls$, it includes PC^{net}, an approximation of cryptocurrency network effect; $attn^{pos}$, a proxy for positive investor attention; $attn^{neg}$, a proxy for negative investor attention, as well as 1-day-lag return of the cryptocurrency excess return. Lastly, $CSMB$ is the size premium in the currency market and $MCAP^{log}$ is the log market capitalization.

Constants are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Dependent Variable	$Ret^{e}_{d_0+d_1}$(%)				
	(1)	(2)	(3)	(4)	(5)
$CryptVal^{u}_{d_0}$	0.033***	0.045***	0.036***	0.019*	0.045
	(6.04)	(7.19)	(5.46)	(1.76)	(1.64)
$CSMB$	-0.096**	0.496***	0.87***	1.42***	2.63***
	(-2.06)	(8.78)	(15.2)	(16.6)	(10.7)
$PC^{net}_{d_0}$	-0.001	0.007*	0.012***	-0.010**	-0.021
	(-0.16)	(1.72)	(2.91)	(-1.54)	(-1.19)
$attn^{pos}_{d_0}$	0.002***	0.002***	0.002***	0.003***	0.005***
	(4.55)	(5.65)	(5.34)	(4.37)	(3.27)
$attn^{neg}_{d_0}$	0.042***	0.021*	0.038**	0.075***	0.046
	(4.47)	(1.88)	(3.38)	(4.17)	(0.93)
Ret^{e}_{d-1}(%)	-0.022**	-0.045***	-0.035***	-0.136***	-0.127***
	(-2.29)	(-3.72)	(-3.65)	(-6.39)	(-3.87)
$MCAP^{log}$[31]	-0.07*	-0.019***	-0.039***	-0.032***	-0.056***
	(-1.82)	(-4.55)	(-8.57)	(-4.87)	(-3.26)
Fixed Effects	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies
R^2	0.003	0.009	0.019	0.026	0.031
$Obs.$	21,266	21,949	21,698	21,809	6,850

[31] Although all the coefficients are negative here, but the correlation between $Ret^{e}_{d_0+d_1}$ is 0.09.

Table 12: Music Sentiment, daily cryptocurrency market returns and volatility under different sentiment environment

This table reports the relation between cryptocurrency return/volatility and music sentiment under different sentiment environment in the period February 1, 2018 to December 31, 2022. The panel regression used are similar to that in Table 5 and 8. For column (1) and (2), the dependent variable is Volwhich is the 30-day rolling standard deviation while the dependent variable used in column (3) and (4) is $Ret^{e}_{d_0+d_1}$, the combined return of day 0 and day 1. For the independent variables, $CryptVal$ is the value of music sentiment derived from equation (4). PC^{net} is an approximation of cryptocurrency network effect; $attn^{pos}$ is a proxy for positive investor attention, and $attn^{neg}$ is a proxy for negative investor attention. For $FearGreed$, it is an industry-standard index that measure the sentiment (fear/greed) in the cryptocurrency market. One-day-lag value of cryptocurrency excess return and Vol are also controlled.

Constants and lags are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Coefficients in columns (1) and (2) are multiplied by 10,000.

Sentiment	Positive	Negative	Positive	Negative
Dependent Variable	Vol_{d_0}	Vol_{d_0}	$Ret^{e}_{d_0+d_1}$(%)	$Ret^{e}_{d_0+d_1}$(%)
	(1)	(2)	(3)	(4)
$CryptVal_{d_0}$			0.026***	0.008***
			(8.91)	(3.70)
$\lvert CryptVal_{d_0}\rvert$	0.076***	0.064***		
	(6.70)	(7.65)		
$PC^{net}_{d_0}$	0.009	0.023***	0.002	0.014
	(1.64)	(2.64)	(1.25)	(6.31)
$attn^{pos}_{d_0}$	0.009***	0.009***	0.001***	0.001***
	(15.3)	(11.9)	(8.473)	(5.95)
$attn^{neg}_{d_0}$	0.155***	0.074***	-0.0002	0.001
	(9.07)	(3.49)	(-0.05)	(0.26)
$FearGreed$	-0.002***	-0.002***	-0.0002***	0.0005***
	(-8.41)	(-5.11)	(-2.84)	(6.52)
Fixed Effects	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies	Cryptocurrencies
R^2	0.0038	0.0037	0.0013	0.0021
$Obs.$	138,966	82,362	127,518	76,956