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Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears

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ABSTRACT

We examine the predictive ability of online investor sentiment for six major cryptocurrency returns. For this, we use two proxies, the FEARS index of Da et al. (2015) and Twitter Happiness sentiment, applying the bivariate cross-quantilogram of Han et al. (2016). Happiness sentiment index significantly predicts Bitcoin return as well as other major cryptocurrencies at the two extreme states of the market and for extreme levels of sentiment. Hence, investors should readjust their portfolios according to the market sentiment and limit their decision on the safe-haven property of Bitcoin. As to FEARS, predictability also exists but is rather pronounced for a low level of sentiment. Overall, Happiness sentiment reveals to be a persistent and robust predictor for most cryptocurrency returns. FEARS index also shows significant predictability of returns, but the predictability is weaker and mainly in the short-term. In summary, our findings provide evidence that online investor sentiment is a significant nonlinear predictor for most major cryptocurrencies returns, suggesting though the superiority of Twitter to Google-based online investor sentiment proxy. Moreover, cryptocurrency returns seem to be driven more by sentiment transmitted through social media than with macroeconomic news, which is in line with the nature of cryptocurrency participants, mainly young individuals computer enthusiasts.

1. Introduction

Cryptocurrencies have experienced tremendous growth in value that overpassed the most substantial historical bubbles over the last three hundred years (Al-Yahyaee et al., 2019). Therefore, both academic researchers and professionals have shown keen interest in understanding the behavior of these new emergent assets. Simultaneously, return predictability has always been the key aspect of the financial literature and revolves around two theories. According to the classical financial theory, markets are efficient (i.e., all the information is fully included in the observed price of the asset), and only fundamental value determines the stock price. The behavioral finance theory asserts that a non-fundamental factor referred to as investor sentiment can also influence future returns. As the most prominent cornerstone in behavioral finance, investor sentiment is a broad concept that includes emotions and moods. Hence it is not observable. Therefore different proxies have been identified by researchers to test their empirical models. Before the inception of the popular composite index by Baker and Wurgler (2006, 2007) and the news-based proxy of Tetlok (2007) and Tetlok et al. (2008),

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Table 1
Descriptive statistics and unit root properties.

	Mean	Std. Dev.	Q5%	Q95%	Skewness	Kurtosis	J-B	ADF	PP	Correlation with Happiness	Correlation with Fear
BTC	0.206	3.965	−6.553	6.345	−0.064	7.334	1092.501***	−37.051***	−37.084***	−0.015	−0.023
ETH	0.174	5.826	−8.553	9.895	0.070	7.352	1102.146***	−37.355***	−37.473***	0.012	0.005
XRP	0.229	7.187	−8.015	9.912	3.121	45.713	108309.2***	−23.388***	−39.147***	0.042	−0.014
LTC	0.183	5.756	−8.145	8.946	1.204	14.471	7985.357***	−36.656***	−36.752***	−0.006	−0.023
XMR	0.259	6.592	−10.472	10.627	1.086	11.656	4629.425***	−38.394***	−38.594***	0.015	0.004
DASH	0.157	5.677	−8.162	8.894	0.810	10.005	3005.023***	−38.394***	−38.521***	0.021	−0.049
HP	0.007	0.044	−0.056	0.075	0.252	6.371	675.103***	−6.016***	−16.344***		
FR	0.002	0.316	−0.491	0.551	0.149	3.013	5.201*	−8.949***	−107.158***		

Note: This table reports the descriptive statistics and unit root properties of the data. Std. Dev. Stands for standard deviations. J-B refers to the Jarque-Bera test with the null hypothesis of normality. The ADF and PP abbreviations stand for the empirical statistics of the Augmented Dicky-Fuller and Phillips and Perron (1988) unit root tests, respectively.
***, **, and * stand for significance at the 1%, 5%, and 10% levels, respectively.

researchers relied mainly on survey-based sentiment measures[1] and single market-related proxies, such as trading volume, turnover rate, and mutual funds flow (Brown & Cliff, 2004). Recently, as argued by Fabozzi (2008), with greater access to online information, Google and Twitter also provide consistent indicators to measure investors' emotions and preferences.

Accordingly, in this paper, our research question is whether online investor sentiment can predict cryptocurrency returns. Many reasons motivate the focus of our research. First, it is not easy to assess the value of cryptocurrencies, given that there is a large controversy on their nature, for example, whether they are a currency, a financial bubble, or simply a digital asset (White et al., 2020). Accordingly, there is no consensus on which factors drive their prices. For this reason, cryptocurrency valuation depends highly on opinions, widely constructed through online engines, such as Google and Twitter. Second, as suggested by Yelowitz and Wilson (2015) and Bouri et al. (2017a), many cryptocurrency traders are individual investors and computer programming enthusiasts, that may lack sufficient trading knowledge.

To answer our research question, we use two online investor sentiment proxies. The first is Twitter Happiness sentiment, an index constructed by the largest social media platform, Twitter. The second is the Financial and Economic Attitudes Revealed by Search of American households (hereafter, FEARS). This later proxy is an index originally constructed by Da et al. (2015) using Google Search Volume and proved to significantly predict future returns of stocks, mutual funds, and bonds (Da et al., 2015; Khan et al., 2019). Several empirical studies used the Twitter Happiness index as a proxy for online investor sentiment and have documented its significant connectedness with stock markets (Sun et al., 2016; Li et al., 2017; Shen et al., 2019 and Zhang, Zhang, Shen, & Zhang, 2018). More particularly, in the cryptocurrency area, Shen et al. (2019) have found that Twitter has a significant causal effect on Bitcoin variance returns. Recently, Kraaijeveld and Smedt (2020) have found that Twitter sentiment predicts the returns of Litecoin, Bitcoin, and Bitcoin Cash significantly. Motivated by these findings, we suggest that Twitter Happiness holds the predictive ability for cryptocurrency returns. For FEARS, we build our hypothesis drawing on two main reasons. First, it has empirically documented in existent studies that Google search causes Bitcoin returns (Burggraf et al., 2019 and Eom et al., 2019) significantly. Second, when examining its construction process, we identified another channel that connects the FEARS index with the cryptocurrency market. More particularly, the word "Gold", as an economic term is mentioned three times in the primitive list[2] of 15 search words constructing the index. Empirical studies show that commodity in general and Gold, in particular, is positively correlated with cryptocurrencies (Naeem et al., 2020). Furthermore, many researchers document the significant role of cryptocurrency as a hedge/safe-haven asset for portfolio diversification that includes stocks (Baur et al., 2012; Bouri et al., 2019; Bouri et al., 2017; Ji et al., 2018; Shahzad et al., 2019). Guesmi, Saadi, Abid, and Ftiti (2019) find significant return spillovers between bitcoin prices and financial variables. Moreover, they suggest that a hedging portfolio that includes stocks, Gold, oil, and Bitcoin performs better than a portfolio without Bitcoin, emphasizing the interdependence between commodities and cryptocurrency. Similarly, the empirical findings of Symitsi and Chalvatzis (2018) show a significant return spillover from commodity and technology equities to Bitcoin. Moreover, recent empirical studies have documented that the price dynamics of Bitcoin and other cryptocurrencies are influenced by macroeconomic news (Corbet et al. 2020a, 2020b).

For methodological design, we first use the ordinary least squares estimations (OLS) and quantile regression analysis (QR) and identify a nonlinear relation between online investor sentiment indexes and cryptocurrency returns. Then, as an advanced nonlinear approach, we utilize the cross-quantilogram framework of Han et al. (2016). We suggest that cryptocurrency traders are more concerned with extreme regimes of sentiment in investors, consistent with the literature referring to high and low sentiment periods (Yu & Yuan, 2011). Likewise, the later methodology allows studying predictability from online investor sentiment to cryptocurrencies across quantiles. Hence our study provides new evidence into investor sentiment-cryptocurrency nexus, based on extreme market movements. We argue that applying QR and cross-quantilogram constitutes a suitable methodology to fit the nonlinear structure of the investor sentiment - cryptocurrency returns relationship.

Our sample consists of daily data that spans from March 7, 2016 to December 29, 2019, and six major cryptocurrencies, namely Bitcoin, Litecoin, Ripple, Dash, Monero, and Ethereum. This sample constitutes currently leading cryptocurrencies that attract the most interest among the academic community and investors (Bouri et al., 2019; Dyhrberg, 2016a; 2016b).

Overall, our empirical findings boil down to two main results. The first is that we find the significant predictive ability of the two online investor sentiment proxies on the cryptocurrencies returns, which confirms our two hypotheses.

Such findings are in line with previous studies using the Twitter Happiness index, giving a more in-depth insight into the relationship across quantiles. More importantly, our results also provide new evidence regarding the FEARS index, which suggests that the household investor index predicts the cryptocurrency returns, complementing the previous literature on the stock market. The second main result is that cryptocurrency return predictability is more pronounced with Twitter happiness sentiment than with the FEARS index. We conclude that cryptocurrency traders seem to be more guided with optimism than with pessimism in their investment decision. Accordingly, such findings are worth taking into consideration by investors when thinking about cryptocurrencies as a safe-haven asset for portfolio diversification.

Hence, our study provides new evidence of the inefficiency of cryptocurrencies by comparing two online investor sentiment proxies within a nonlinear framework. More importantly, we also investigated the nonlinear predictive ability of the FEARS index for six major cryptocurrencies, unlike most existing studies that are focused on Bitcoin behavior.

The study is structured into six sections. A review of related literature is presented in section 2. The description of the data and the methodologies will be detailed in the two subsequent sections. Then, in section 5, we exhibit and discuss our findings, and we conclude

[1] Survey-based sentiment measures such as the consumer sentiment of Michigan University and the American Association of Individual Investor (AAII).

[2] To be further explained in data section.

in section 6.

2. Literature review

This section explains how investor sentiment predicts returns as supported by previous literature. First, we begin with the stock markets. Then, we move to the cryptocurrency markets.

2.1. Theoretical and empirical studies related to the stock market

Up to 1970, the efficient market hypothesis (EMH) ruled financial theory. The EMH stipulated that the stock price should reflect fundamental value based on rational and representative agents since any deviation can be easily corrected due to arbitrage. Almost two decades later, stock markets were marked by some stylized facts during specific periods of crashes, crises, and bubbles[3] that could not be explained through the EMH. A new theory subsequently emerged, which indicated that the sentiment of investors could also influence future prices. Comparable to the traditional theory based on rationality, representativeness, and arbitrage, behavioral finance presented an alternative approach based on heterogeneity and limits to arbitrage. De Long et al. (1990) provide a popular theoretical model, where two kinds of investors could represent the economy. In essence, rational investors analyze the information available according to fundamental values and are able to distinguish between useful and non-useful information. In contrast, irrational investors are generally unsophisticated agents that lack experience and required trading knowledge to analyze the information. They concluded that irrational investors trade not according to fundamentals, rather on their emotions and moods and can influence prices, leading to its deviation from the fundamental value. This deviation may persist over time because arbitrage is limited by transaction costs and risks of short selling. Hence, prices are not determined only by fundamental factors but also by market opinions (i.e., how an agent perceives the market and reacts accordingly). This latter non-fundamental factor is referred to as investor sentiment. Other theoretical sentiment models, including Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999), and De Bondt (2000, pp. 65–69), suggest a short-term impact of investor sentiment on stock returns. Whereas Barberis and Thaler (2003) state that the impact can be extended to a longer horizon.

To sum up, investor sentiment as a significant determinant of stock prices is supported by many theoretical models, though more in the short-term than in the long-term. However, whether it is a contrarian (predicts negatively) or momentum (predicts positively) predictor of future stock returns, it is still a question of debate. Particularly, Warther (1995) argued that the debate is essentially due to the uncertainty on the appropriate time frame chosen for predictability, whether short-term, long-term, or all horizons.[4]

For a long time, empirical evidence was limited to the American stock market because of the long history of investor sentiment proxies. As a concept related to behavioral and psychological aspects, investor sentiment could not be measured by a specific observable variable. Therefore, several proxies are experimented with in empirical literature. Some are survey-based, and others are market-related (Brown & Cliff, 2004; Baker and Wurgler (2006, 2007)). Tetlock (2007) was the first to link media news to the stock market, based on textual sentiment analysis. He found that negative media sentiment revealed by media news causes lower future market prices. Whereas, Tetlock et al. (2008) found that the relevant information on firm fundamentals revealed by media news has no causal effect on market prices. Recently, with the growing progress of the internet and social media, researchers' interest has been shifting towards online indicators such as Google and Twitter. Da et al. (2015) developed the FEARS index to measure American households' perceptions of the future state of the market and the whole economy. In recent research studies, there is a fast-growing knowledge to extract sentiment from news, taking advantage of advanced textual analysis approaches, through several social media platforms. Among the existing, Kraaijeveld and Smedt (2020) pointed out that Twitter is the most popular data source that provides suitable indicators combining both news and sentiment.

2.2. Investor sentiment and predictability of the cryptocurrency market

This section discusses to what extent investor sentiment can predict cryptocurrency returns, as well.

Shleifer and Summers (1990) describe investment as a social process, meaning that sentiment investors who are noise traders because they are not driven by good information but interpret any fact as good information, will influence others to hop on the bandwagon,[5] causing price deviations. This "bandwagon effect" might be persistent because of the continuous flow of new investors, driven by increasing sentiment. Particularly, Banerjee (1992) shows that the new investors, even though rational, will rely on public information rather than on their private information, hence leading to herd behavior. Moreover, Banerjee (1992) argues that herding behavior implies that sentiment predicts future returns positively. We predict that this phenomenon might also occur in the cryptocurrency market, as investors are mainly young and enthusiasts, and herding behavior matters in the cryptocurrency market. The debate of herding behavior in cryptocurrency was first introduced by Bouri et al. (2017a). They argue that cryptocurrency has some specific features. Cryptocurrency participants are mainly individuals, young that lack knowledge and experience regarding trading, even those who are computer programming enthusiasts as previously indicated by Yelowitz and Wilson (2015), we suggest that they are not

[3] The crash of 1987, the internet bubble of 2000, the subprime crisis of 2007 and the recent global financial crisis of 2008–2009.

[4] See also, Fisher and Statman (2000); Baker and Wurgler (2007), Schmeling (2009) and Han and Li (2017) for a discussion of the theoretical effects.

[5] This effect is characterized in literature by the "bandwagon effect".

necessarily well informed about trading. Therefore, it is more plausible that the valuation of cryptocurrencies depends more on opinions, which is constructed mainly through online engines, such as Google and Twitter, rather than other financial or economic factors. Specifically, weak legal framework and a lack of quality information, combined with the nature of crypto traders as discussed earlier, maybe robust reasons to state that, similarly to "noise traders" in the stock market, one can cautiously suggest describing crypto investors as "noise crypto traders".[6]

Empirically, Bouri et al. investigate 14 cryptocurrencies. They found no herding behavior with the static approach, while a significant result when considering structural breaks when economic policy uncertainty is high. They argue that this occurs because investors shift from risky to safe-haven investments. Vidal-Tomás and Farinós (2018) provide evidence of asymmetric herding behavior since herding exists only during the bearish market. Kaiser and Stôkl (2020) contribute to this debate by focusing on the "transfer currency" concept, suggesting a new measure of belief dispersion based on the beta. They conclude a significant robust herding behavior. Philippas et al. (2020) study the effect of exogenous informative factors on the herding intensity. We argue that the way herding behavior matters in the cryptocurrency is strong proof of the substantial role of investor sentiment for cryptocurrency. The empirical evidence that studies this relationship use especially causality tests. The first one was initiated by Balcilar et al., who use a non-parametric causality-in-quantile test to study whether the trading volume can predict Bitcoin return and volatility. They find that volume can predict returns during normal conditions of the market but not its extremes. Bouri et al. extend their work by applying a copula-quantile causality approach to examine the causality between trading volume and seven major cryptocurrencies. They find a significant Granger causality between trading volume and extreme negative and positive returns of all cryptocurrencies. Using linear and nonlinear Granger causality tests, Shen et al. (2019) find a significant causality relation between the number of tweets and Bitcoin realized volatility and trading volume but not returns. Recently, Kraaijeveld and Smedt (2020), through textual sentiment analysis and using bilateral Granger-causality analysis, show that Twitter bots predict the returns of Litecoin, Bitcoin, and Bitcoin cash significantly.

Related works cited above focus more on extracting sentiment from social media and then studying its connectedness to cryptocurrency returns using causality analysis. Accordingly, we aim to study whether two distinct online proxies of investor sentiment can predict cryptocurrency returns by overpassing causality analysis to more informative approaches.

Our main hypothesis in this work is that online investor sentiment is a nonlinear predictor of cryptocurrency returns. Particularly, we investigate two hypotheses:

H1. Online investor sentiment can predict cryptocurrency returns

Particularly, we are interested in testing the predictive ability of two sentiment proxies. Hence we divide H1 into two sub-hypotheses:

H1-a. Happiness sentiment index can predict cryptocurrency returns

H1-b. FEARS index can predict cryptocurrency returns

It has been documented in the literature that investor sentiment is nonlinearly linked to asset return. Particularly, Lee et al. (2002) have even argued that investor sentiment constitutes the most important factor explaining nonlinearity in asset prices. This statement was further supported by many other researchers such as Chen and Lee (2013), Ni et al. (2015), Namouri et al. (2018), and Balcilar et al. (2018). Moreover, few papers have studied return predictability in the cryptocurrency market through nonlinear models such as nonlinear Granger causality tests in Shen et al. (2019) and a copula quantile causality in Bouri et al.

Accordingly, we support the second hypothesis as follows:

H2. The relationship between online investor sentiment and cryptocurrency returns is nonlinear.

3. Data

3.1. Cryptocurrency returns

Daily closing prices of six large cryptocurrencies are collected from https://coinmarketcap.com/. These are Bitcoin (BTC), Litecoin (LTC), Ripple (XRP), Etherum (ETH), Monero (XMR), and Dash (DASH). Our sample spans from March 7, 2016–December 29, 2019. We use log-transformed returns across our analyses. In brief, summary statistics in Table 1 reveal that overall, cryptocurrencies exhibit homogeneous return behavior that ranges from 15.7% for DASH to 25.9% for XMR. All cryptocurrencies are non-normal and stationary. XRP is the most volatile, whereas BTC is the least volatile.

3.2. Online investor sentiment proxies

We use two distinct online investor sentiment proxies: the Twitter Happiness index and the FEARS index. We collect Twitter happiness index data from http://hedonometer.org/index.html, which is generated from the Twitter Gardenhose feed database with over 50 million Twitter posts. The index is formulated from nearly 10,000 sentiment related words mentioned in randomly selected Twitter posts. The FEARS index is the investor sentiment proxy originally constructed by Da et al. (2015) to measure American household expectations. It is the sum of 118 words searched on Google. The index was initially constructed in daily frequency. Further,

[6] It is a simple suggestion, far from a theoretical prediction, we are aware of the need of theoretical models based on the heterogeneous hypothesis which has not yet been questioned in the cryptocurrency literature, at our knowledge.

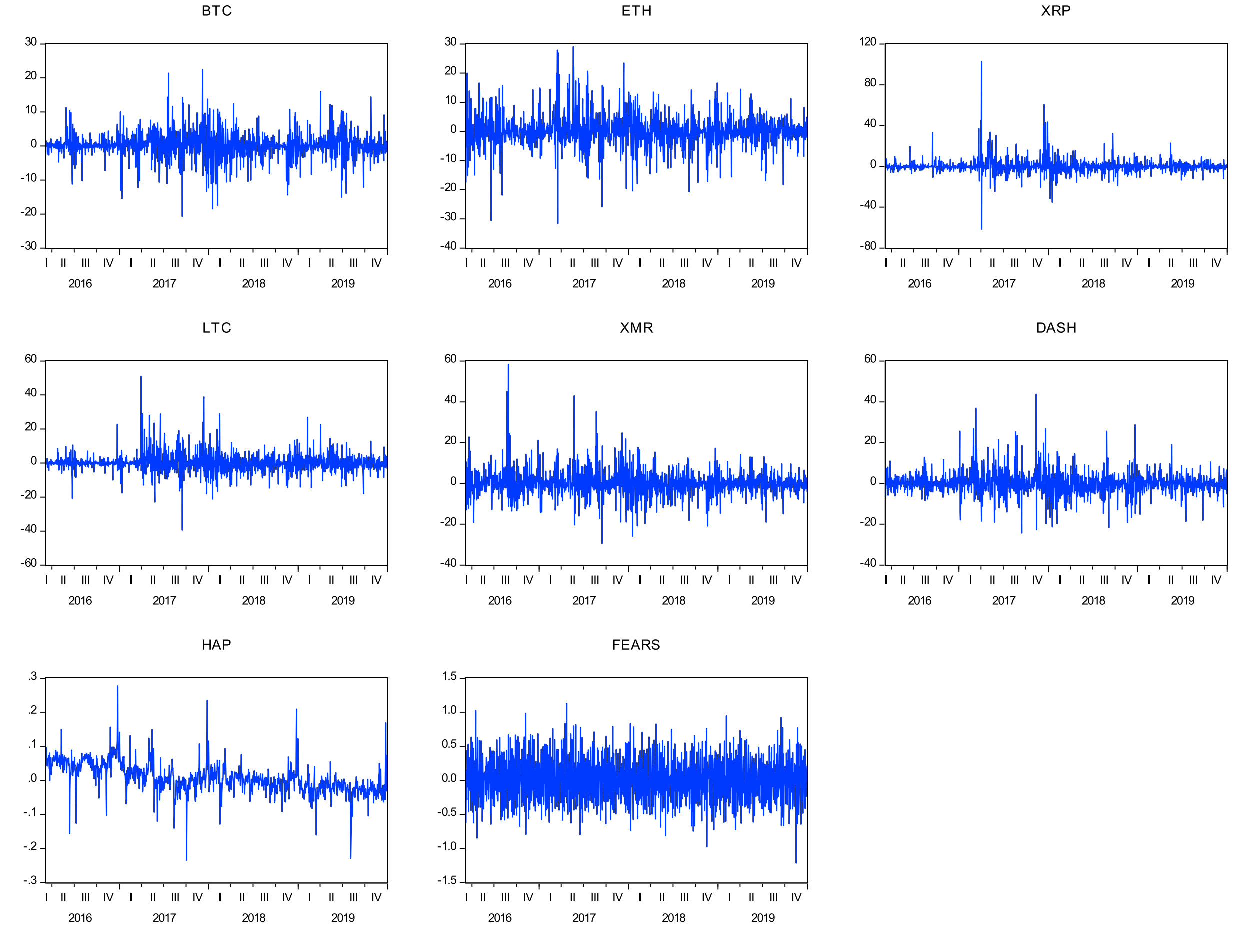

Fig. 1. Time series plots of daily return series of cryptocurrencies and deseasonalized Happiness and FEAR sentiment indexes. BTC (Bitcoin), ETH (Ethereum), XRP (Ripple), LTC (Litecoin), XMR (Monero), DASH (Dash), HAP (Happiness sentiment), and FEAR (Fear sentiment)
Note: The daily sample data span March 7, 2016 to December 29, 2019.

Khan et al. (2019) have used and extended the dataset to construct a weekly FEARS index. Following Da et al. (2015) and Li et al. (2017), we deseasonalize the Twitter Happiness index and FEARS index, hence avoiding the influence of seasonality on the investor sentiment–cryptocurrency returns relationship. We present the time series plot for the evolution of cryptocurrencies and the two investor sentiment proxies in Fig. 1.

As indicated in Table 1, both sentiment proxies have positive mean returns, while Fear is the most volatile. Nonlinearity and stationarity are proved by J-B test statistic and ADF and PP tests, respectively. Finally, the unconditional correlation results provide evidence that the Happiness sentiment index is almost positively correlated to cryptocurrency returns, whereas FEARS is negatively correlated. These findings are in line with the hypothesis that positive sentiment (optimism) is associated with high returns, whereas negative sentiment or pessimism (revealed by high values of FEARS) leads to decreased cryptocurrency returns. Hence, it is worth studying how online investor sentiment can predict cryptocurrency returns.

4. Methodologies

4.1. OLS and quantile regression (QR) methodology

In this study, we first employed OLS and QR to determine whether investor sentiment predicts cryptocurrency returns. The QR is initially introduced by Koenker and Bassett (1978) and it is widely used in finance literature (Demirer et al., 2017; Pedersen, 2015; Li & Wu, 2014; Badshah, 2013; Alagidede & Panagiotidis, 2012; Bauret al., 2012; Chiang & Li, 2012). QR has many advantages. First, it is robust to outliers and heteroskedasticity (Koenker & Hallock, 2001; Koenker, 2005). Also, it directly addresses asymmetric effects, where lower (upper) quantiles associate bad (good) states (Ding et al., 2016). According to Linnemann and Winkler (2016), QR classifies different ex-ante regimes (recessions and expansions) by assuming a specific model to address nonlinearity. Huang et al. (2015) illustrated that the sentiment index predicts portfolio returns in terms of mean but not in the median. Therefore, this study considers the following linear predictive model

$$y_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1} \tag{1}$$

where y_{t+1} represents the excess return and x_t represents (Happiness sentiment or FEARS). The conditional mean given by OLS is as follow:

$$E(x_t) = \alpha + \beta x_t \tag{2}$$

Also, the conditional distribution function of y_{t+1}as proposed by quantile regression at quantile τ given regression x_t is defined as

$$Q_t(x_t) = \alpha_\tau + \beta_\tau x_t + F^{-1}_{\varepsilon_{t+1}}(\tau) \tag{3}$$

where, $F_\varepsilon$is the error distribution, and β_τ and α_τ are the parameters. The estimated coefficients of the τ^{th} conditional QR is as follows:

$$\widehat{\beta}^{\tau} = arg \Big| min_{\alpha_\tau, \beta_\tau \in R} \sum_{t=1}^{T} \rho_\tau(y_{t+1} - (\alpha_\tau + \beta_\tau x_\tau)) \tag{4}$$

where the sample size is denoted by T and ρ_τ is the check function defined as $\rho_\tau(\varepsilon) = \tau\varepsilon$ if $\varepsilon \geq 0$ and $\rho_\tau(\varepsilon) = (\tau - 1)\varepsilon$ otherwise. Therefore, the least absolute deviation method is a particular case of QR.

4.2. Cross-quantilogram (CQ) methodology

The cross-quantilogram (CQ) methodology was proposed recently by Han et al. (2016), as a way to model the dependence and spillover among the two-time series at stationary levels for dissimilar conditional quantiles. Besides that, Han et al. (2016) also developed a Box-Ljung Q-type statistic test in order to test the directional predictability between the time series. The CQ is a generalized extended version of the quantilogram statistic, which Han et al. (2016) extend by broadening it to accommodate bivariate joint distributions, which were univariate in Linton and Whang (2007) quantilogram static methodology.

The CQ is developed to measure the lead-lag causal association from 'any given quantile' to "any given quantile", rather dependent on the conditional variances of the distribution of both the explanatory variables and response variable. It's an advantageous extreme quantile approach in as it investigates the spillover or predictability for large lags possible by studying different possible combinations of cross-correlation. Han et al. (2016) defined CQ as the cross-quantile for the quantile-hit processes;

$$\rho_\alpha(k) = \frac{E[\Phi_{\alpha1}(x_{1,t} - q_1(\alpha_1))\Phi_{\alpha2}(x_{2,t-k} - q_2(\alpha_2))]}{\sqrt{E[\Phi^2_{\alpha1}(x_{1,t} - q_1(\alpha_1))]}\sqrt{E[\Phi^2_{\alpha2}(x_{2,t} - q_2(\alpha_2))]}} \tag{5}$$

for k = 0, ±1, ±2, …, for the time lags, where $(_a(\mu) = 1\ [\mu < 0] - \alpha$ is an indicator function, $[x_{i,t} - q_i(\alpha_i)]$ represents a quantile-hit process, and $\rho_\alpha(k)$shows a quantile-based cross-correlation estimator across investor sentiment and cryptocurrency returns that accounts for time lag effects among the series.

Accordingly, the CQ measures serial dependency between the two series at different quantile levels. Considering $\alpha = (\alpha_1, \alpha_2) = (\alpha_{\text{RV}}, \alpha_{\text{Ret}})$ as an example, $\rho_\alpha(1)$ captures the cross-correlation between the realized volatility being above or below quantile $q_{\text{RV}}(\alpha_{\text{RV}})$ at time t and the future return being above or below quantile $q_{\text{Ret}}\ (\alpha_{\text{Ret}})$ at time $t+1$. Thus, (1) = 0 implies that no predictability or time-lag effect is identified between the two time series of return at $\alpha = q_{vol}\ (\alpha_{bs})$ or $q_{ret}\ (\alpha_{bs})$. On the contrary, if (1) $\neq$ 0, there exists a 1-day directional predictability from one series to another series. The CQ sample analog in the inverse direction is as follow:

$$\widehat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T}\Phi_{\alpha1}(x_{1,t} - q_1(\alpha_1))\Phi_{\alpha2}(x_{2,t-k} - \widehat{q}_2(\alpha_2))}{\sqrt{\sum_{t=k+1}^{T}\Phi^2_{\alpha1}(x_{1,t} - \widehat{q}_1(\alpha_1))}\sqrt{\sum_{t=k+1}^{T}\Phi^2_{\alpha2}(x_{2,t-k} - \widehat{q}_2(\alpha_2))}} \tag{6}$$

for k = 0, ±1, ±2, … In Eq. (2), $\widehat{q}_i(\alpha_i)$is the unconditional sample quantile of $x_{i,t}$. The CQ as defined in Eq. (2) considers a lead-lag quantile dependence of one time series (x_2) to another time series (x_1) for a given quantile pair (α_1, α_2), thus measure the directional predictability of x_2 to x_1 via $\rho_\alpha(k)$.

Furthermore, based on $\rho_\alpha(k)$, the quantile version of the Ljung-Box-Pierce statistic withH_0:$H_0 : \rho_\alpha(k) = 0$ for all $k\ \varepsilon$ 1, …, p, against $H_1 : \rho_\alpha(k) \neq 0$ for some k 1, …, p as:

$$\widehat{Q}^{(p)}_\alpha = \frac{T(T+2)\sum_{k=1}^{p}\widehat{\rho}^2_\alpha(k)}{T-k} \tag{7}$$

where, a portmanteau test of directional predictability is represented by $\widehat{Q}^{(p)}_\alpha$ from one-time series to another according to the quantile pair $\alpha = (\alpha_1, \alpha_2)$ and p lags.

5. Empirical results

The cross-quantilogram, as an extreme nonlinear dependence approach, is based on some preliminary tests to justify its use. This

Table 2
Linear Granger causality test.

	HAP does not GC cryptocurrency returns	Order of VAR(p)	FEAR does not GC cryptocurrency returns	Order of VAR(p)
BTC	1.406	6	6.751	6
ETH	12.053*	6	1.527	6
XRP	3.451	6	11.014*	6
LTC	4.511	6	8.888	6
XMR	4.956	6	6.248	6
DASH	14.883*	8	1.742	6

Note: The table reports the F-statistics for the "no Granger causality" restrictions imposed on a linear vector autoregressive (VAR) model under the null hypotheses H_0. The order (p) of the VAR is determined by the Akaike Information Criterion (AIC). * indicates rejection of the null hypothesis at the 10% level of significance.

Table 3
Nonlinear Granger causality (Diks & Panchenko, 2006) test.

	HAP does not GC cryptocurrency returns	Order of VAR(p)	FEAR does not GC cryptocurrency returns	Order of VAR(p)
BTC	0.739	6	0.807	6
ETH	1.568	6	0.818	6
XRP	0.996	6	0.637	6
LTC	1.910**	6	0.617	6
XMR	0.517	6	0.719	6
DASH	0.249	8	0.505	6

Note: The table reports the statistics for the "no Granger causality" restrictions imposed on a nonlinear model under the null hypotheses H_0. ** indicates rejection of the null hypothesis at the 5% level of significance.

study first uses both linear and nonlinear Granger causality test, then an OLS and Quantile regression. Table 2 and Table 3 reports whether Happiness sentiment and FEARS Granger cause cryptocurrency returns. As can be seen, excluding ETH and Dash, Happiness does not Granger cause the return for four cryptocurrencies. Moreover, FEARS only Granger causes XRP returns. We argue that such a finding might suggest a nonlinear Granger causality. Therefore, we also conducted a nonlinear Granger causality test. However, unexpectedly, the results accept the null hypothesis, except for Happiness Granger causing LTC returns. As our second hypothesis in this paper is to investigate the nonlinear relationship between investor sentiment and cryptocurrency returns, we, therefore, do not limit our econometric methods to the nonlinear Granger causality test. However, we also investigated other different techniques for the purpose of a deeper analysis of the nonlinear relationship.

We report, in the next section, the results of OLS and QR.

5.1. OLS and quantile regression

We report estimations for both happiness sentiment and FEARS index in Table 4 and Table 5, respectively. In each table, Panel A reports the estimations for OLS, whereas Panel B reports the estimations for QR. Consistent with the linear Granger causality test, the estimations for OLS regression are all insignificant, which constitutes additional proof of nonlinearity.

Panel B in Table 4 indicates that Happiness sentiment significantly predicts the returns of BTC, XRP, LTC, and XMR at lower quantiles (up to 25th quantiles), and it significantly predicts returns for all the cryptocurrencies except BTC, at the extreme higher quantile. Notably, Happiness has no significant predictability during normal times, but when the market is bearish and more strongly in the bullish state. As to the FEARS index, it predicts Dash return at the two extreme tails, BTC at 25th quantile but strongly predicts XRP at all quantiles upper than 25th level. Unlike previous studies showing the influence of macroeconomic news on Bitcoin price (Corbet et al., 2020a) and cryptocurrencies prices (Corbet et al., 2020b), we find that the FEARS index weakly predicts cryptocurrencies prices, except for Dash and XRP.[7] In a nutshell, we find that the predictive ability of Happiness has a forecasting power at both tails and strongly at the extreme higher quantile for all the cryptocurrencies other than BTC, while FEARS predicts only Dash and XRP returns. Overall, our findings support our two hypotheses when using Happiness sentiment, i.e., H1-a and H2, implying that Happiness sentiment can predict cryptocurrency returns, and this predictability is nonlinear, as shown by QR estimations. However, when using the FEARS index, our hypotheses appear to be weakly supported.

Constructing a sentiment index based on macroeconomic news, Corbet et al. (2020b) find that Bitcoin return is influenced by this news, which implies that this new financial asset is maturing. Moreover, Corbet et al. (2020a) highlight a cryptocurrency market heterogeneity implying diverse reactions to the same news. We argue that this might be a reason why the FEARS index predicts only DASH and XRP returns.

[7] In unreported results, we also used weekly data and we found that FEARS predicts these two cryptocurrencies only in one extreme tail and not both.

Table 4
OLS and Quantile regression estimations of Happiness sentiment for cryptocurrencies.

	BTC	ETH	XRP	LTC	XMR	DASH
Panel A						
OLS						
Intercept	0.215**	0.163	0.179	0.188	0.243	0.137
HP_1	−1.344	1.574	6.911	−0.763	2.199	2.773
R^2	0.022%	0.014%	0.178%	0.003%	0.022%	0.046%
Panel B						
I) 5th Quantile						
Intercept	−6.562***	−8.493***	−8.072***	−8.161***	−9.917***	−8.218***
HP_1	−0.775	−2.998	20.735***	6.891	−27.225**	4.862
R^2	0.003%	0.033%	0.665%	0.051%	1.011%	0.033%
II) 25th Quantile						
Intercept	−1.242***	−2.339***	−2.162***	−2.127***	−2.712***	−2.445***
HP_1	7.996***	−5.352	−5.826**	11.226***	−5.144	0.664
R^2	0.723%	0.080%	0.127%	0.743%	0.125%	0.003%
III) 50th Quantile						
Intercept	0.203***	−0.071	−0.317***	−0.144	−0.038	−0.091
HP_1	1.914	−1.084	−0.642	2.569	4.207	1.904
R^2	0.094%	0.008%	0.005%	0.056%	0.066%	0.011%
IV) 75th Quantile						
Intercept	1.778***	2.442***	1.713***	2.123**	3.011***	2.528***
HP_1	−2.574	3.920	−0.604	−6.085**	13.057***	7.778**
R^2	0.064%	0.008%	0.002%	0.153%	0.832%	0.272%
V) 95th Quantile						
Intercept	6.336***	9.737***	9.514***	9.075***	10.610***	8.811***
HP_1	−0.647	39.630***	36.432***	−16.983**	24.687***	22.401***
R^2	0.015%	1.739%	0.750%	0.267%	0.958%	0.944%

Note: Panel A presents estimations for OLS regression, whereas Panel B presents estimations for quantile regression at 5th, 25th, 50th, 75th, and 95th quantile. *, **, *** represents significance at 10, 5, and 1%, respectively.

Table 5
OLS and Quantile regression estimations of FEARS index for cryptocurrencies.

	BTC	ETH	XRP	LTC	XMR	DASH
Panel A						
OLS						
Intercept	−6.527***	0.174	0.230	0.184	0.258	0.159
FR_1	−0.214	0.095	−0.329	−0.416	0.086	−0.875*
R^2	0.002%	0.003%	0.008%	0.052%	0.002%	0.237%
Panel B						
(I) 5th Quantile						
Intercept	−18.010***	−8.508***	−8.168***	−8.116***	−10.389***	−7.992***
FR_1	7.763	−1.307	−2.337	−0.743	−0.868	−2.096
R^2	2.637%	0.203%	0.316%	0.075%	0.045%	0.326%
(II) 25th Quantile						
Intercept	−1.147***	−2.296***	−2.132***	−2.140***	−2.771***	−2.502***
FR_1	−0.826**	−0.941**	−1.227***	−1.287***	−1.149**	−0.615
R^2	0.257%	0.168%	0.236%	0.472%	0.254%	0.097%
(III) 50th Quantile						
Intercept	0.227***	−0.114	−0.333***	−0.071	−0.039	−0.111
FR_1	−0.243	−0.338	−0.721***	−0.367	0.010	−0.481
R^2	0.048%	0.053%	0.213%	0.053%	0.000%	0.058%
(IV) 75th Quantile						
Intercept	1.743***	2.493***	1.692***	2.114***	3.201***	2.636***
FR_1	0.296	0.055	−0.574	−0.281	−0.116	0.394
R^2	0.047%	0.001%	0.112%	0.017%	0.000%	0.022%
(V) 95th Quantile						
Intercept	6.397***	10.028***	9.679***	9.366***	10.609***	8.928***
FR_1	0.864	2.797	−1.174	−3.215	0.694	2.336*
R^2	0.152%	0.312%	0.032%	0.588%	0.043%	0.529%

Note: Panel A presents estimations for OLS regression, whereas Panel B presents estimations for quantile regression at 5th, 25th, 50th, 75th, and 95th quantile. *, **, *** represents significance at 10, 5, and 1%, respectively.

Fig. 2. Heatmaps of cross-correlation between daily Happiness sentiment and cryptocurrency returns.
Note: These figures show the CQ in the form of heat maps. The quantile levels with no significant directional predictability are set to zero. The colored rectangles are the predictable regions where the Box–Ljung test statistic is statistically significant. In each heatmap, the horizontal axis represents Happiness sentiment quantiles, while the vertical axis represents cryptocurrency return quantiles.

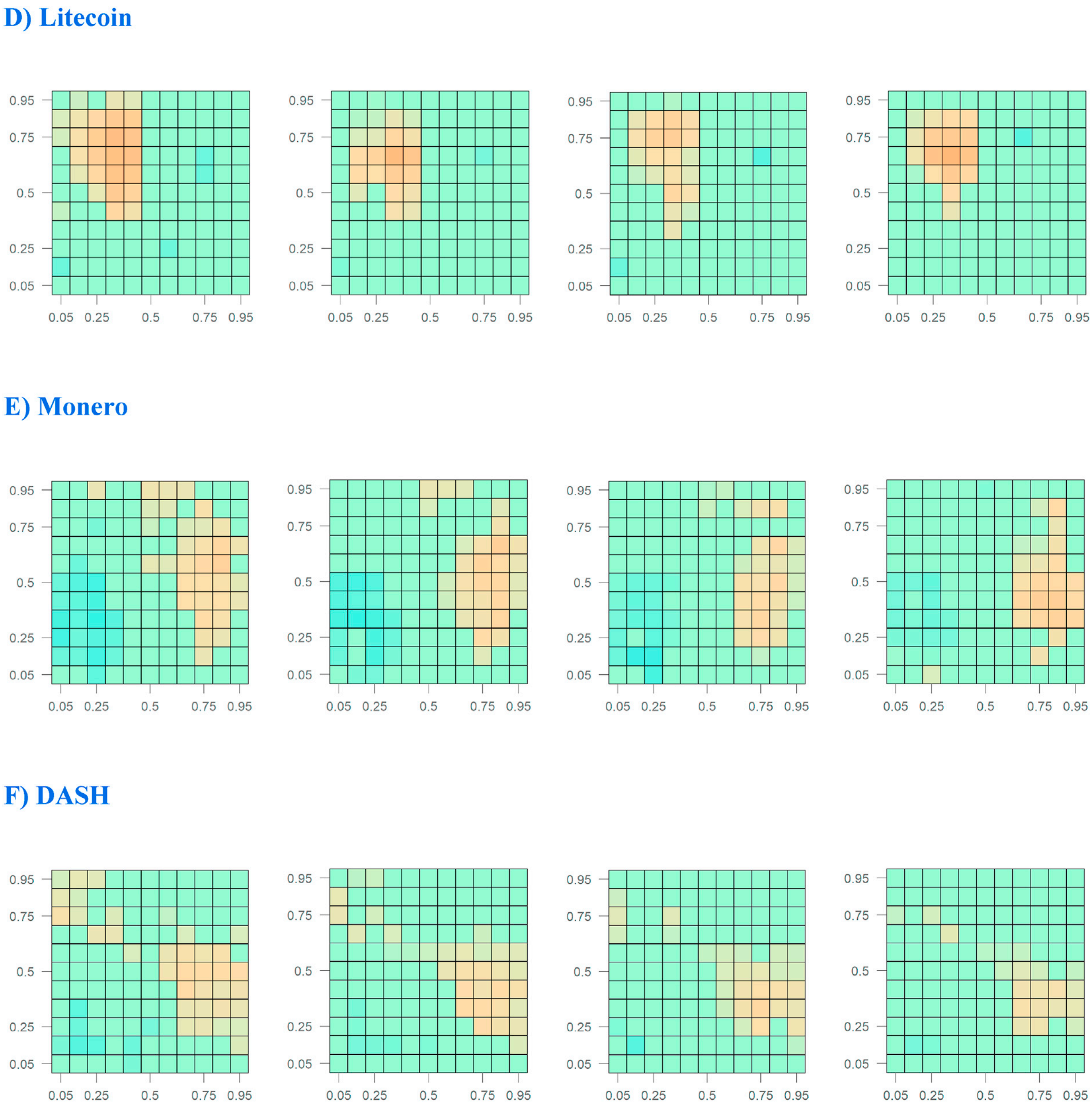

Fig. 2. . (*continued*).

5.2. *Cross-quantilogram*

For a more in-depth insight into the nonlinear dependence of cryptocurrency returns to online investor sentiment, we use the cross-quantilogram. Results are presented in the form of heat maps, where the horizontal axis is designed for quantiles of the online investor sentiment proxy, and the vertical axis is designed for quantiles of cryptocurrency returns. Heat maps are preferred for tables to avoid reporting too many coefficients. Figs. 2 and 3 show only significant dependence for Happiness sentiment and FEARS index, respectively.

Fig. 2 shows that Happiness appears to be a strong return predictor for all the cryptocurrencies. We find a significant positive dependence in the upper left corner for Bitcoin, Ripple, Litecoin, and to a lesser extent, DASH. That means that negative future returns follow previous low happiness sentiment. Particularly for Dash, Monero, and ETH on the right side, high previous Happiness is followed by future positive returns, consistent with the momentum hypothesis of investor sentiment in stock markets. A negative dependence is also found for Monero in the left lower corner, suggesting an opposite relation between low Happiness and Monero return when the market is bearish.

Fig. 3. Heatmaps of cross-correlation between daily FEAR sentiment and cryptocurrency returns.
Note: These figures show the CQ in the form of heat maps. The quantile levels with no significant directional predictability are set to zero. The colored rectangles are the predictable regions where the Box–Ljung test statistic is statistically significant. In each heatmap, the horizontal axis represents FEAR sentiment quantiles, while the vertical axis represents cryptocurrency return quantiles.

Fig. 3. . (*continued*).

One more finding that needs to be highlighted is that predictability from Happiness sentiment to cryptocurrency returns is not only in the short run but persists up to nearly one month (lag 22). Whereas, Georgoula et al. (2015) found only a short-term correlation between positive Twitter sentiment and Bitcoin's price. Likewise, unlike sentiment behavior findings in the stock market and, more importantly, in the cryptocurrency market (Karalevicius et al. (2018), no reversal pattern is shown across investment horizons. For instance, Kent, Hirshleifer, and Subrahmanyam (1998) have reported a short overreaction of cryptocurrency prices due to sentiment, which is slightly followed by a further correction.

We call that high FEARS is likely to be more associated with distress time than in good or normal time for the FEARS index. Whereas low FEARS might reveal less search for specific terms, reflecting neutral or positive expectations, which is a more expected attitude during good times. An overall sight in Fig. 3 reveals much fewer colored quantiles than previously, suggesting hence weaker significant predictability from FEARS to cryptocurrency returns. Notably, almost a negative dependence is shown, which is mostly pronounced on the left side of the heatmap. This suggests that a particularly low FEARS index predicts cryptocurrencies returns negatively.

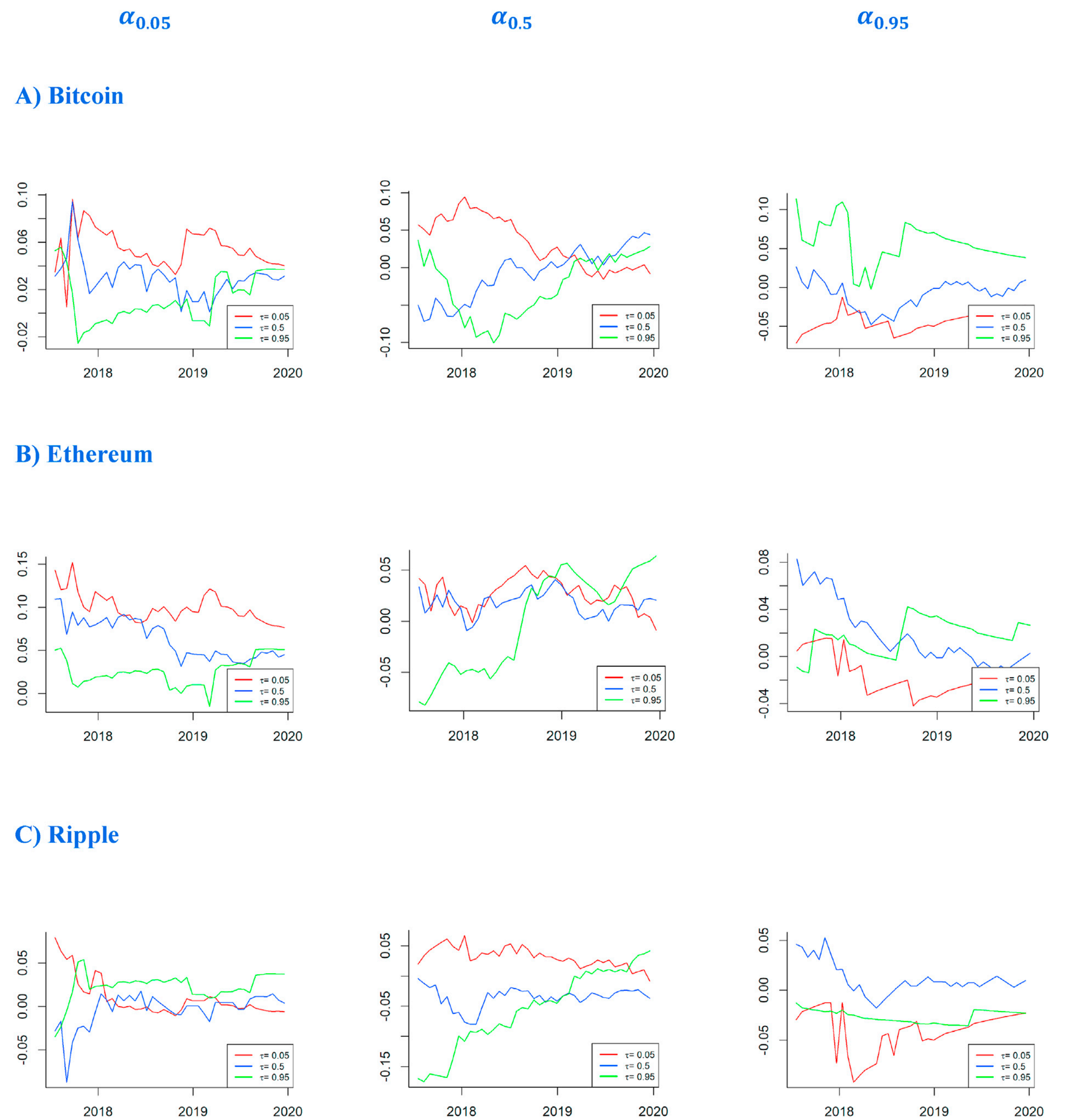

Fig. 4. Recursive CQ between daily Happiness sentiment and cryptocurrency returns.
Note: The vertical (horizontal) axis represents the quantile hits for the cryptocurrency market (time). The starting year of the rolling window is marked on the horizontal axis. The left, middle, and right columns, respectively, show the 5%, 50%, and 95% quantiles for the Happiness sentiment while, the red, blue, and green lines represent the 5%, 50%, and 95% quantiles for the cryptocurrency returns. Lag p = 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

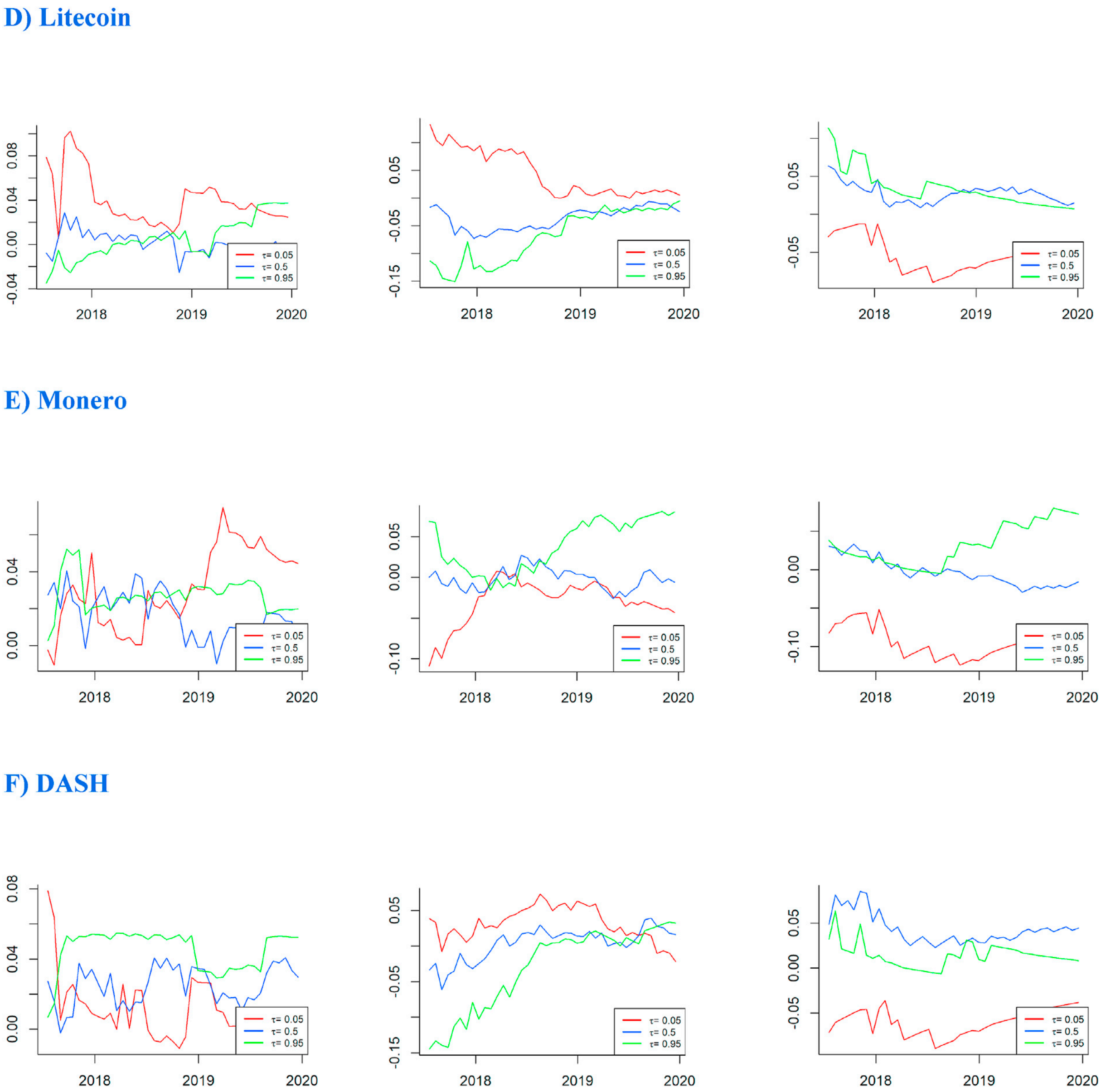

Fig. 4. . (*continued*).

Furthermore, only a few quantiles are red, suggesting a rare positive dependence between the FEARS index and cryptocurrencies returns, contrary to Happiness findings.

Contrary to Happiness sentiment, predictability from FEARS does not exceed at best two days (lag 2). This leads to confirm that the FEARS index is a short-term return predictor (Da et al., 2015). In line with Da et al. (2015) and Khan et al. (2019), who find a significant causal effect of the FEARS index on stock market returns, our findings suggest that FEARS seem to predict cryptocurrency returns as well, though the significance is much weaker than in the stock market.

However, comparing the two proxies used in this study, Twitter Happiness sentiment appears to be a stronger predictor than FEARS, not only in the short term but almost up to one month (lag 22). We argue that our findings support the substantial, informative social

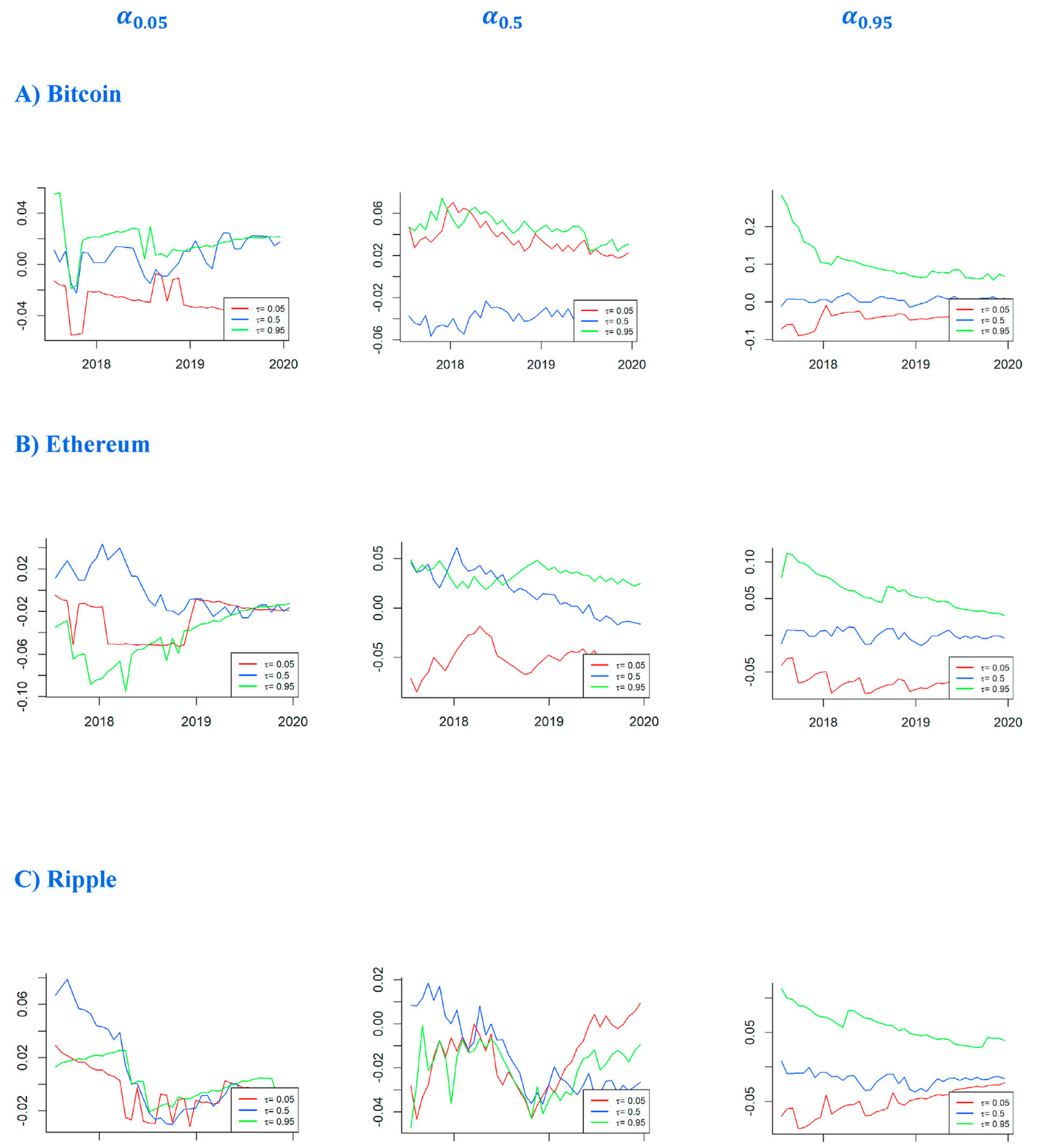

Fig. 5. Recursive CQ between daily FEAR sentiment and cryptocurrency returns.
Note: The vertical (horizontal) axis represents the quantile hits for the cryptocurrency market (time). The starting year of the rolling window is marked on the horizontal axis. The left, middle, and right columns, respectively, show the 5%, 50%, and 95% quantiles for the FEAR sentiment while, the red, blue, and green lines represent the 5%, 50%, and 95% quantiles for the cryptocurrency returns. Lag p = 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

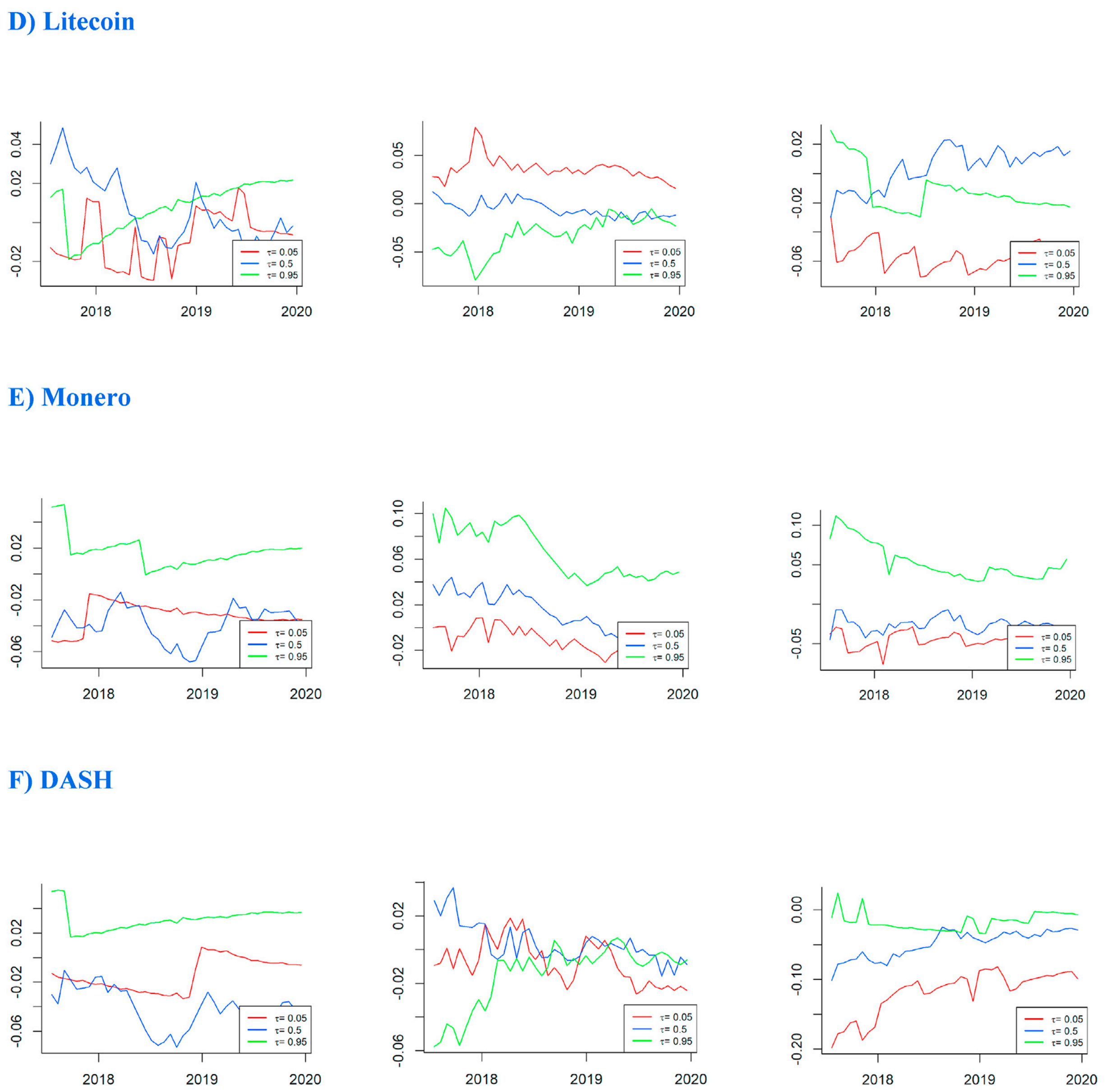

Fig. 5. . (*continued*).

media role for the cryptocurrency return (Kraaijeveld & Smedt, 2020), compared to macroeconomic news. Though, Corbet et al. (2020a, b) find that Bitcoin and other cryptocurrencies are influenced by some specific macroeconomic news while reporting an heterogeneous reaction due to specific characteristics.[8]

In the last part of our predictability analysis, we used a recursive sampling approach with a sample window that increases by one day for the estimation in each step. Fig. 4 and Fig. 5 plots the predictive pattern from Happiness (FEARS) to cryptocurrency returns for the extreme lower, the middle, and the upper quantiles. When the market is bearish (red line), extreme low Happiness (α = 5%) positively predicted returns of BTC, ETH, and LTC, whereas very high Happiness (α = 95%) is negatively associated with returns. As to FEARS, as previously, the co-dependence is almost weaker in magnitude, and predictability is most pronounced when the market is bullish (green line). Contrary to static analysis, rolling window analysis shows that the FEARS index can predict more major cryptocurrencies.

[8] Corbet et al. (2020a) classify digital assets into three categories: currency, protocol and decentralized application and also whether they are mineable or not-mineable. They find that the digital market is diverse and not all the cryptocurrencies can be comparable to Bitcoin.

Meanwhile, looking at predictability during the sample period for both sentiment proxies reveals that predictability varies over time. However, we are merely unable to detect whether the efficiency of major cryptocurrencies increases or decreases, as suggested by other researchers claiming that some cryptocurrencies are becoming efficient as long as the market matures.

6. Conclusion

We aim to study whether online investor sentiment can predict six major cryptocurrencies returns. We use two investor sentiment proxies, a social media-based index, the Twitter Happiness sentiment, and a Google-search-based index, the FEARS index of Da et al. (2015). We adopt an extreme quantile approach, the cross-quantilogram, to provide a deeper insight into the nonlinear relationship.

Our findings show that sentiment, particularly as proxied by the Happiness sentiment index, predicts significantly Bitcoin return as well as other major cryptocurrencies at the two extreme states of the market and for extreme levels of sentiment. Hence, investors should readjust their portfolios according to the market sentiment, as stated by the "flight-to-quality" behavior hypothesis in literature, and no more limit their decision on the safe-haven property of Bitcoin. Klein et al., 2018 find that Bitcoin is negatively correlated to Gold during market downturns. Moreover, our findings imply that Bitcoin can be considered an investment asset than as a currency, other major cryptocurrencies like LTC, XRP and ETH seem to be investment assets well, as their return dynamics are influenced by market sentiment. Furthermore, we find that cryptocurrency return is more driven by Happiness sentiment than by the FEARS index, which is in line with the nature of the cryptocurrency participants that are mostly young individuals who are more guided by the social media sentiment transmission than macroeconomic news.

As to the significant nonlinear relationship, our findings are in line with lee et al. (2002), Chen and Lee (2013), Ni et al. (2015), Namouri et al.(2018), Balcilar et al. (2018) and Shen et al. (2019).

We used different lags in our analysis, from one day to nearly a month (lag 22). Overall, our findings reveal that Happiness is a strong predictor of all the cryptocurrency returns that can persist up to 22 days. FEARS also appear to predict returns, but predictability is weaker, heterogeneous across the cryptocurrencies, and mainly in the short horizon. Such a conclusion suggests Twitter's superiority, as the largest social media platform to Google engine, in proxying online investor sentiment and predicting cryptocurrency returns.

Author statement

Muhammad Abubakr Naeem; Conceptualization, Methodology, Software, Formal analysis, Writing, Original Draft. Imen Mbarki; Conceptualization, Writing, Original Draft. Syed Jawad Hussain Shahzad; Conceptualization, Methodology, Writing – Review and editing, Supervision.

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