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Does Twitter Happiness Sentiment predict cryptocurrency?

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Abstract

We examine the predictive ability of Twitter Happiness Sentiment for six major cryptocurrencies using daily data from August 7, 2015 to December 31, 2019. At first instance, our results conclude a significant nonlinear relationship between Twitter Happiness Sentiment and cryptocurrencies. The nonlinear dependence structure is further enhanced when using the quantile-on-quantile (QQ) analysis, which indicates that high and low sentiment predicts returns of five cryptocurrencies. These findings are statistically and economically significant.

KEYWORDS

cryptocurrencies, linear and nonlinear Granger causality, quantile-on-quantile, Twitter Happiness Sentiment

1 | INTRODUCTION

Classical financial assets are valued based on their fundamental value, including dividends, earnings and on the concept of arbitrage. Comparably, a cryptocurrency is a digital entity with no physical representation. It is neither associated with any commodity, nor a firm, and no government has superior authority on it (Shen, Urquhart, & Wang, 2019). Moreover, it is managed through specific systems such as blockchain, Initial Coin Offerings (ICOs), and decentralized schemes. All of these specific features make the cryptocurrency's fundamental value harder to assess (Jiang, Nie, & Ruan, 2018). Accordingly, numerous recent studies examine cryptocurrency predictability (Ciaian, Rajcaniova, & Kancs, 2016; Kristoufek, 2013; Urquhart, 2016, among others). Kristoufek (2013) found that searches on Google and Wikipedia significantly cause Bitcoin prices. More specifically, Urquhart (2016) and Nadarajah and Chu (2017) confirmed that Bitcoin returns are predictable, rejecting the Efficient Market Hypothesis. Other studies have examined the causality of trading volume and technical trading to cryptocurrency returns (Balcilar, Bouri, Gupta, & Roubaud, 2017; Bouri, Lau, Lucey, & Roubaud, 2018; Gerritsen, Bouri, Ramezanifar, & Roubaud, 2019; Huang, Huang, & Ni, 2019).

Most research on cryptocurrency predictability is inspired by stock return predictability. There is a large literature on stock returns predictability, which includes several predictors, both fundamental and nonfundamental. Among nonfundamental predictors, investor sentiment constitutes the largest branch. It is a nonobservable factor that includes emotions, sentiments, and behavioral attitudes. Many theoretical models in Behavioral finance stipulate the significant role of investor sentiment in predicting stock returns (Barberis, Shleifer, & Vishny, 1998; De Bondt, 2000; De Long, Shleifer, Summers, & Waldmann, 1990; Hong & Stein, 1999, among others).

In order to validate the theoretical predictions, researchers have tried several proxies of investor sentiment, as it is a nonobservable variable. These include direct proxies as consumer confidence index and the American Association of Individual Investors (AAII) Indice, or indirect proxies including either individual market-related proxies or a composite index such as the most popular Baker and Wurgler index (2006, 2007). Other news related sentiment proxies also exist (Kraaijeveld & Smedt, 2020; Tetlock, Saar-Tsechansky, & Macskassy, 2008). Using different proxies of investor sentiment, the significant role of sentiment in predicting stock returns is confirmed. Consequently, it is a relevant question to study whether investor sentiment can predict cryptocurrency returns. Particularly, in this paper, we aim to study the connection between a new online investor sentiment and cryptocurrency returns. We use the Twitter Happiness index, which is an index provided by Twitter. The latter is the largest social media platform, among all the existing. Many reasons motivate our research. First, according to empirical studies confirming the existence of herding behavior in the cryptocurrency market (Bouri, Gupta, & Roubaud, 2019; Kaiser & Stöckl, 2020; Vidal-Tomás, Ibáñez, & Farinós, 2018)[1] as well as the overreaction hypothesis (Chevapatrakul & Mascia, 2019) and the small price bias (Aloosh & Ouzan, 2019), we argue that this suggests that investor sentiment might have a substantial role in predicting cryptocurrency returns. Second, as argued by Frijns, Verschoor, and Zwinkels (2017), online information is becoming a suitable tool to measure investors' emotions and preferences. Indeed, sophisticated information technology has reduced the cost of internet access and mobile use, which results in massive use of social media platforms. Hence, cryptocurrencies, as a digital asset, would be strongly affected by social media news. Third and more particularly, several studies show that Twitter has a significant impact on financial markets (Li, Shen, Xue, & Zhang, 2017; Naeem, Farid, Faruk, & Hussain Shahzad, 2020; Sun, Lachanski, & Fabozzi, 2016; Zhao, 2020). In the crypto market, Shen et al. (2019) show that Twitter significantly causes Bitcoin variance returns. Likewise, Kraaijeveld and Smedt (2020), using a textual technique analysis, find that Twitter bots are significant predictors of Bitcoin, Litecoin, and Bitcoin cash returns. Particularly, Li et al. (2017), Zhao (2020), and Naeem et al. (2020) find a significant causal relationship between Twitter happiness sentiment index and stock market variables.

Since its creation in 2009, as pointed out by Corbet, Lucey, Urquhart, and Yarovaya (2018), Bitcoin was the focus of many research studies, for the sake of understanding how this nonclassical asset, exhibiting such tremendous trading volume, behaves. Over recent years, especially since 2017, the market value of other leading cryptocurrencies, such as Ethereum, Ripple, Litecoin, Monero, Dash, and Stellar, has increased substantially (Bouri et al., 2018). Consequently, researchers are shifting their interest towards these leading cryptocurrencies, too (Baumohl, 2018; Bouri et al., 2018, 2019; Zhao, 2020). Likewise, in this research, we aim to study whether Twitter's happiness sentiment can predict returns of six major cryptocurrencies.

We first use linear and nonlinear causality tests, and then a quantile-on-quantile analysis following Sim and Zhou (2015).

Our contributions can be summarized in two points. First, we use Twitter happiness sentiment as a new proxy for investor online happiness sentiment and study its dependence with five major cryptocurrencies returns, other than Bitcoin. Specifically, we find that happiness sentiment predicts returns of five cryptocurrencies at different quantiles. Our findings are in line with previous studies (Balcilar, Bekiros, & Gupta, 2017; Balcilar, Gupta, & Kyei, 2018; Chevapatrakul & Mascia, 2019; Shen et al., 2019). Thus, we provide new evidence of cryptocurrency predictability based on online investor sentiment, contrary to other existing studies that support efficiency in the cryptocurrency market, such as Le Tran and Leirvik (2019). Second, our study uses a novel quantile approach, the QQ analysis of Sim and Zhou (2015). Previous literature utilized other quantile-based approaches, such as causality in quantile test in Balcilar, Bekiros, and Gupta (2017) and Balcilar et al. (2018) and the copula quantile-causality test in Bouri et al. (2018). However, our study is the first to use the QQ analysis to examine the ability of online investor sentiment to predict cryptocurrency returns. Furthermore, motivated by recent literature indicating the growing importance of other cryptocurrencies, besides Bitcoin, among crypto traders as well as academics (Baumohl, 2018; Bouri et al., 2018; Zhao, 2020), we use other major cryptocurrencies.

Section 2 describes the empirical methodology. Then, we report and discuss the empirical results in Section 3, and we conclude the study in Section 4.

2 | DATA AND METHODOLOGY

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 covered by Twitter Gardenhose feed database, such as love, laughter, celebration, winning. These selected words are then individually rated on a 1 (extremely negative) to 9 (extremely positive) and 5 (neutral). It should be noted that happiness is more pronounced during weekends and holidays). Therefore, studying the raw happiness in analyses might be biased. Consequently, we deseasonalized the raw happiness series from the weekday effect and the national holiday effect. Following Da, Engelberg, and Gao (2015) and Li et al. (2017), using an OLS model, we regress the raw happiness index on the weekday and holidays' dummies. The residual constitutes then the happiness sentiment index (HAP), which we use in our further analyzes. The deseasonalized time series allows us to examine the underlying relationship between cryptocurrencies and the Twitter Happiness sentiment independent of the influence of seasonality. We present the evolution of the deseasonalized Twitter Happiness (HAP) sentiment in Figure 1.

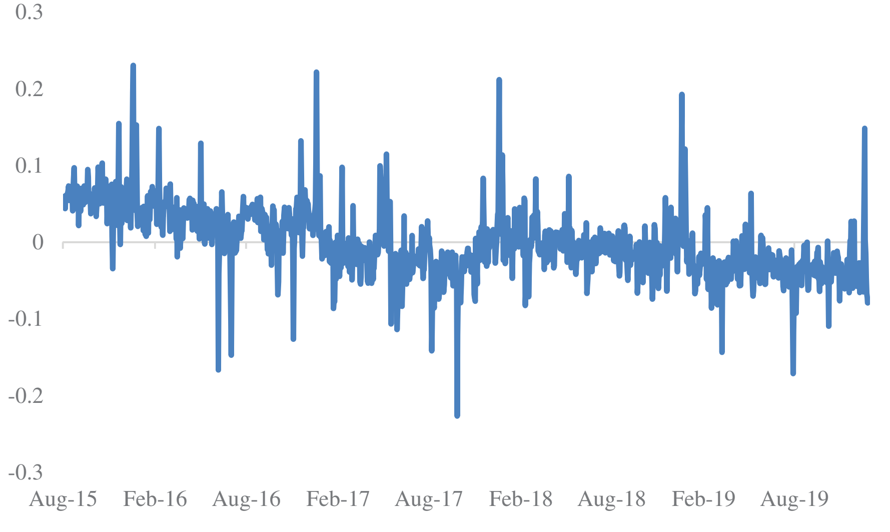

FIGURE 1 Time-series graph of the deseasonalized Daily Twitter Happiness index

We collect daily closing prices for cryptocurrencies from https://coinmarketcap.com/. We choose six major cryptocurrencies based on their popularity and large market capitalization in the cryptocurrency market. To extract data for a longer duration, we collect data for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Monero (XMR), and Dash (DASH) from August 7, 2015 to 31st December 2019.

As a starting point, we used linear and nonlinear causality tests to analyze the link between the crypto market and the Twitter happiness index. Granger causality test (Granger, 1969) test was used for linear causality test which tests the link between two variables, in this case, the Twitter happiness index (y_t) and the crypto market (x_t). We can write down this as follows:

$$y_t = \alpha_1 + \sum_{i=1}^{n} b_i x_{t-i} + \sum_{j=1}^{m} \gamma_i y_{t-j} + \epsilon_{1t}$$

$$= \alpha_2 + \sum_{i=1}^{n} \theta_i x_{t-i} + \sum_{j=1}^{m} \delta_i y_{t-j} + \epsilon_{2t} \tag{1}$$

The uncorrelated error terms in the above equation are denoted by ϵ_{1t} and ϵ_{2t}. If the lag of y_t predict the current value x_t that shows y_t "Granger causes" x_t (for details see Granger, 1969). For the nonlinear model, we follow the Péguin-Feissolle and Teräsvirta (1999) framework by estimating a Taylor approximation as follows:

$$y_t = \int^{*} \left(y_{t-1},...,y_{t-q},...x_{t-1},...,x_{t-n},\theta^{*}\right) + \epsilon_{t,} \tag{2}$$

Though, it is assumed to represent the causal link among y_t and x_t based on the hypothesis that x_t does not granger cause y_t. To measure noncausality, we follow Péguin-Feissolle and Teräsvirta (1999) and Péguin-Feissolle, Strikholm, and Teräsvirta (2013), we test Equation (2) in contradiction of

$$y_t = \int^{*} \left(y_{t-1},...,y_{t-q},\theta\right) + \epsilon_{t,} \tag{3}$$

In the next step, we used quantile-on-quantile regression to examine the nonlinear relationship further. Following the Sim and Zhou (2015), we study the associations between Twitter happiness index and the crypto market. Through this, we can examine the relationship between cryptocurrency returns and the Twitter happiness index that might fluctuate over different quantiles. As a first step, we model the ϑ-quantiles of cryptocurrency returns as a function of Twitter happiness index as follows:

$$CR_t = \beta^{\vartheta} THI_t + \alpha^{\vartheta} CR_{t-1} + \epsilon_t^{\vartheta} \tag{4}$$

In the above equation the quantiles of the crypto market returns (CR_t) are denoted by ϑ whereas the THI_t represents the Twitter happiness index. The error term with zero ϑ-quantile is indicated with ϵ_t^{ϑ}. As we do not have preceding information related to crypto market returns to Twitter happiness index, so we presume that β^{ϑ}(.) is not known. The relationship between ϑ-quantiles crypto market returns and θ- quantiles of Twitter happiness index is represented as THI_t^{θ}. With unknown parameter β^{ϑ}(.), we can write the expansion of first-order Taylor as follows:

$$\beta^{\vartheta}(THI_t) \approx \beta^{\vartheta}\left(THI_t^{\theta}\right) + \beta^{\vartheta'}\left(THI^{\theta}\right)\left(THI_t - THI^{\theta}\right) \tag{5}$$

In the above equation the marginal effect is $\beta^{\vartheta'}$ which is derived from $\beta^{\vartheta}(THI_t)$ was related to THI. In the above equation, $\beta^{\vartheta}(THI_t)$ and $\beta^{\vartheta'}(THI^{\theta})$ parameters are doubly indexed in ϑ, and θ. We can see that THI^{θ}, is the function of θ only. Subsequently, $\beta^{\vartheta}(THI_t^{\theta})$ and $\beta^{\vartheta'}(THI^{\theta})$ are the utility of ϑ and THI^{θ} and as THI^{θ} is a function of θ which suggests that $\beta^{\vartheta}(THI_t^{\theta})$ and $\beta^{\vartheta'}(THI^{\theta})$ are the functions of ϑ, and θ, respectively. After this perception, if we redefine $\beta^{\vartheta}(THI_t^{\theta})$ and $\beta^{\vartheta'}(THI^{\theta})$ as $\beta_0(\vartheta,\theta)$ and $\beta_1(\vartheta,\theta)$ correspondingly. We can rewrite Equation (5) as:

$$\beta^{\vartheta}(THI_t) \approx \beta_0(\vartheta,\theta) + \beta_1(\vartheta,\theta)\left(THI_t - THI^{\theta}\right) \tag{6}$$

After substituting Equation (6) from Equation (4), we get,

$$CR_t = \beta_0(\vartheta,\theta) + \beta_1(\vartheta,\theta)\left(THI_t - THI^{\theta}\right) + \epsilon_t^{\vartheta} \tag{7}$$

The estimates of Equation (7) dependence structure between crypto market returns and Twitter happiness index over the dependence among their particular quantiles.

3 | EMPIRICAL FINDINGS

Table 1[2] reports linear and nonlinear Granger causality results between Twitter Happiness Index (HAP) and six major cryptocurrencies returns, namely, Bitcoin, Ethereum, Ripple, Litecoin, Monero, and Dash. We find an insignificant linear Granger causality relationship between happiness sentiment and cryptocurrencies. However, the nonlinear Granger causality test was significant at 10% for BTC but at 1% for all the five remaining cryptocurrencies. Overall, results confirm that the Twitter Happiness index significantly influences cryptocurrency returns. These findings are in line with Shen et al. (2019) that the number of tweets has a significant nonlinear relationship with Bitcoin.

In order to have a better insight into the nonlinear dependence structure between happiness sentiment index and cryptocurrency returns, we use a robust quantile approach, which is the QQ analysis. We plot the results in Figure 2. Panel A shows the slope coefficient $\hat{\boldsymbol{\beta}}_{(\boldsymbol{\vartheta},\boldsymbol{\theta})}$ at different values of the $\boldsymbol{\vartheta}$ and $\boldsymbol{\theta}$. Panel B reports the statistical significance at 5%. At first glance, there is significant predictability from happiness sentiment to cryptocurrencies returns, but the relationship varies across quantiles of the conditional distribution of cryptocurrencies and happiness

TABLE 1 Causality test results for linear and nonlinear model

Null hypothesis	Linear GC Granger Stat	Nonlinear GC Taylor-based Stat
HAP –/→ BTC	0.6599	1.6249*
HAP –/→ ETH	0.8664	3.0610***
HAP –/→ XRP	0.067	3.1051***
HAP –/→ LTC	0.6452	1.6902**
HAP –/→ XMR	1.0404	2.1549***
HAP –/→ DASH	0.08277	2.3066**

Note: The table reports linear and nonlinear causality results, where HAP (Twitter Happiness Index), BTC (Bitcoin), ETH (Ethereum), XRP (Ripple), LTC (Litecoin), XMR (Monero), and DASH (Dash).
*Significance at 10%.
**Significance at 5%.
***Significance at 1%.

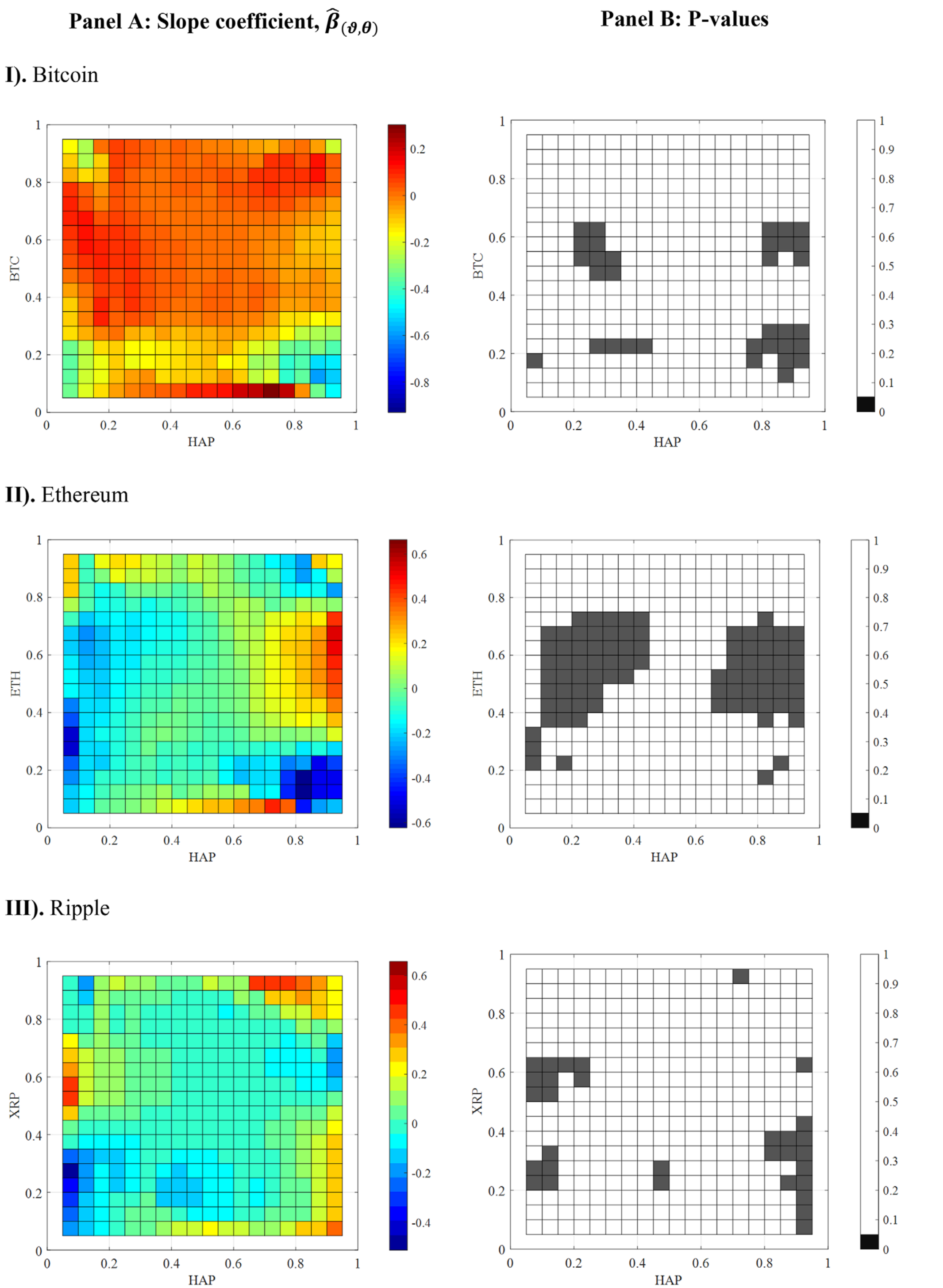

FIGURE 2 QQR estimates between cryptocurrency returns and Twitter happiness sentiment. Panel A: Slope coefficient, $\hat{\beta}_{(\vartheta,\theta)}$. Panel B: *p*-values. (I) Bitcoin, (II) Ethereum, (III) Ripple, (IV) Litecoin, (V) Monero, (VI) DASH. The left panel in each figure shows the slope coefficients, and the right panel figures show the *p*-values. *p* values at a 5% significance level are shown in black color

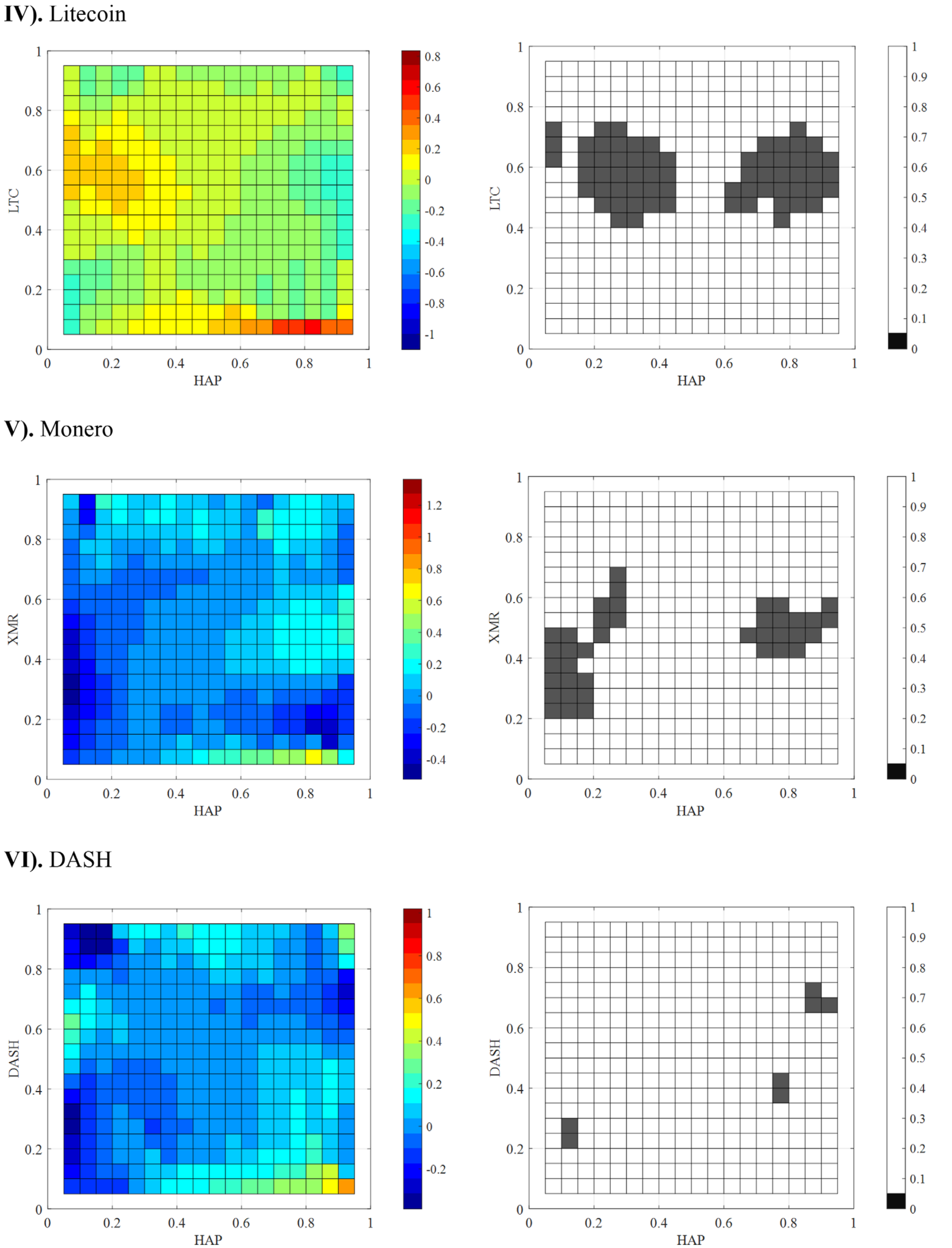

FIGURE 2 (Continued)

sentiment. More specifically, high and low happiness sentiment predicts cryptocurrency returns significantly. However, there is no significant predictability from happiness to returns when the market is bearish or bullish. According to significance through p-values, we can observe three families of dependence structure from happiness sentiment to cryptocurrency returns, namely large, medium, and small predictability. The large predictability family extends on several quantiles at the two tails includes Litecoin, Ethereum, and Monero. The medium predictability family that concerns the extreme tails includes Bitcoin and Ripple. Finally, the small predictability, that concerns only one or two quantiles includes Dash.

Etheurum return appears to be predictable by happiness sentiment, during the normal condition of the market (from 0.30 to 0.75 quantiles), at the right tail of happiness (above 0.65 quantiles) and the left tail (from 0.05 to 0.40). More particularly, the high sentiment is positively related to ETH return, whereas low sentiment is negatively related.

We observe that Litecoin has a similar dependence structure, but with an opposite effect. In other words, the high sentiment is negatively related to LTC return, while low sentiment is positively related. For Monero, the structure is a little bit different. The high sentiment is positively related to the central quantile of returns (from 0.40 to 0.60), while low sentiment is negatively related to returns. For medium predictability family, there is some heterogeneity across the two cryptocurrencies. The high sentiment is found to be negatively related to Bitcoin returns during the bearish and normal market state. Whereas low sentiment is positively related to returns at 0.20 and (0.45–0.65) quantiles. These results corroborate with Balcilar, Bouri, et al. (2017), who find a similar relationship between trading volume and returns of Bitcoin. On the other hand, the high sentiment is positively related to the return of Ripple, around the median. However, the low sentiment is negatively related to returns at the whole central distribution. Finally, Dash appears to be the least predictable cryptocurrency in our sample. This is in contrast with Bouri et al. (2019), who find a significant causality from trading volume to Dash during the bearish state of the market.

Our results are somewhat in line with other predictability studies such as Al-Yahyaee et al. (2019), who found that Litecoin is the most inefficient while DASH is the most efficient. They argue that liquidity and volatility drive efficiency, depending on the quantiles. Though, it seems that the difference in predictability among cryptocurrencies is common to many empirical studies in this area. For example, Tran 2019 found that Litecoin is the most efficient, while Ripple is the least efficient. Aloosh and Ouzan (2019) examined the psychology of cryptocurrencies and concluded that cryptocurrency traders' behavior seems to be biased, and the price level itself strongly affects its impact on their beliefs. That is, investors react differently to news, according to the price level of the cryptocurrency, whether it is high or low. We add that the differences between cryptocurrencies in terms of nature and age might also affect the way they react to the news. For example, BTC was created and so traded since 2009, while Monero and Dash were developed later in 2014.[3]

To sum up, QQ analysis shows that happiness sentiment can predict cryptocurrency returns during normal market conditions. Examining lower and higher quantiles, we conclude that happiness sentiment weakly predicts cryptocurrency returns during bullish and bearish states of the market. Our results corroborate with some existing studies that are based on a similar methodology. Using a quantile autoregressive model, Chevapatrakul and Mascia (2019) find that Bitcoin returns are predictable, arguing that as markets are inefficient, current prices overreact to the previous price due to the presence of sentiment traders in the cryptocurrency market. Overall, our findings are in line with Balcilar et al. (2018) and Bouri et al. (2018), who, using quantile-based methodologies, find that investor sentiment is a good predictor for US stock returns.

4 | CONCLUSION

This paper studies the predictive ability of the Twitter happiness sentiment for six major cryptocurrencies. Our results reveal no linear Granger causality, but a significant nonlinear Granger causality across the whole sample. For further evidence regarding the nonlinear relation, we utilize a quantile-on-quantile analysis. Our findings indicate that happiness sentiment is a significant predictor for five cryptocurrencies, except Dash. Furthermore, the ability of happiness sentiment, to be a significant predictor of cryptocurrencies, is conditional on whether the market is bearish, normal, or bullish. Hence, in line with Li et al. (2017), Zhao (2020) and Naeem et al. (2020) regarding stock markets, we provide evidence that there exists interdependence between online investor sentiment and cryptocurrency returns. Particularly, the structure dependence is nonlinear and is conditional on whether happiness sentiment is high or low. We may interpret our findings as additional evidence of inefficiency in the cryptocurrency market and that online investor sentiment drives the price movement of cryptocurrencies. Accordingly, researchers, investors, and portfolio managers should consider the happiness sentiment as a predictor of cryptocurrencies, and hence undertake profitable trading strategies. Nevertheless, other alternatives for econometric methodologies, as well as investor sentiment proxies, are needed for robust conclusions.

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ENDNOTES

[1] See Banerjee (1992) for a discussion of the relation between herding behavior and investor sentiment.

[2] For brevity, we skip the descriptive statistics. However, the estimations are available upon request.

[3] See Chuen, Guo, and Wang (2017) for a description of cryptocurrencies.

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