International Review of Economics and Finance 75 (2021) 723–746

Contents lists available at ScienceDirect

International Review of Economics and Finance

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

Comparing search-engine and social-media attentions in finance research: Evidence from cryptocurrencies

Yue Li [a], John W. Goodell [b], Dehua Shen [a,*]

[a] College of Management and Economics, Tianjin University, Tianjin, 300072, PR China
[b] College of Business, University of Akron, Akron, OH, 44325, USA

ARTICLE INFO

JEL classification:
G14
G4

Keywords:
Cryptocurrencies
Investor attention
Granger causality
Social media
Twitter
Google
Wavelet testing

ABSTRACT

There is considerable interest in the impact of investor attention on investment returns, especially for cryptocurrencies. However, previous research does not distinguish between search-engine attention and social-media forms of attention—even though this distinction is emphasized by marketing professionals. Professional marketers emphasize that attention is optimized by combinations of social-media and search-engine presence. We investigate the bi-directional causalities, and concomitant frequencies, between cryptocurrency returns and investor attention, comparing cryptocurrency sensitivity to Twitter tweets and the intensity of Google searches, as well as combinations of Twitter and Google. For 27 cryptocurrencies, we use a non-parametric wavelet Granger causality test to incorporate multiple time horizons. We also employ Diebold and Yilmaz spillover testing to assess respective pairwise influence between attention measures and respective cryptocurrencies. Results indicate a preponderance of bidirectional Granger causality for the great majority of cryptocurrencies, with the impact of Twitter on cryptocurrencies being shorter term. Consistent with expectations, we identify that bi-directional causalities, and spillovers, of cryptocurrencies with investor attention are significantly more evident for proxies of investor attention that are combinations of social media (Twitter) and search engine intensity (Google), rather than either one of these forms alone. Our results have applicability to a broad range of investor attention studies.

1. Introduction

While search engine results signal important patterns of attention (Zhang & Tang, 2016), promotion of attention is considered by marketers to work best with a combination of search-engine and social-media marketing (Xiang & Gretzel, 2010; Yang, Lin, Carlson, & Ross, 2016). Consequently, we contend finance scholars interested in investor attention should consider more closely how attention proxies are formed.

Considering the heightened role of investor attention on cryptocurrencies, we consider a focus on these currencies as ideal for our investigation. We compare the bi-directional causality of cryptocurrency returns with investor attention, alternatively proxying investor attention with Twitter, as a form of social media, and Google Trends, as a form of search-engine intensity. We also investigate differing weightings between Twitter and Google. We examine 27 cryptocurrencies, using a non-parametric wavelet Granger causality test (NWGC) as an ideal tool that incorporates multiple time horizons. We also examine spillovers between cryptocurrencies and

* Corresponding author. College of Management and Economics, Tianjin University, No.92 Weijin Road, Nankai District, Tianjin, 300072, PR China.

E-mail addresses: yuelee@tju.edu.cn (Y. Li), johngoo@uakron.edu (J.W. Goodell), dhs@tju.edu.cn (D. Shen).

https://doi.org/10.1016/j.iref.2021.05.003
Received 14 September 2020; Received in revised form 29 April 2021; Accepted 14 May 2021
Available online 20 May 2021
1059-0560/

Google, Twitter, and weighted combinations of search-engine and social-media attentions.

The relationship between cryptocurrencies and investor attention, having received considerable recent attention (e.g., Dastgir, Demir, Downing, Gozgor, & Lau, 2019; Kristoufek, 2013; Ibikunle, McGroarty, and Rzayev, 2020; Shen, Urquhart, & Wang, 2019; Zhang & Wang, 2020), reflects scholarly interest both in cryptocurrencies and in the impact of the Internet and social media on financial markets. Most studies on the impact of investor attention on cryptocurrencies (Dastgir et al., 2019; Kristoufek, 2013; Ibikunle, McGroarty, and Rzayev, 2020; Shen et al., 2019; Zhang & Wang, 2020) have used as attention proxies alternatively either search-engine activity or social-media activity as measures of investor attention. This follows a number of studies on various topics that use similar Internet-based measures (Cheng, Chiao, Wang, Fang, & Yao, 2021; Goodell and Huynh, 2020; Guo, Finke, & Mulholland, 2015; Hu, Xiao, Goodell, & Shen, 2021; Ibikunle, McGroarty, and Rzayev, 2020; Li, Zhang, & Yuan, 2019; Rakowski, Shirley, and Stark, 2018). While studies have alternatively used various forms of search-engine intensity or social-media intensity as proxies for investor attention, few studies offer comprehensive comparison regarding whether search-engine intensity or social-media intensity is the best capture of investor attention. We address this gap by providing a detailed comparison of the alternative roles of Twitter (social media) and Google Trends (search-engine) in impacting, or being impacted by, 27 cryptocurrencies across multiple time horizons.

We consider that cryptocurrencies, and by extension other financial assets, are likely more sensitive in response to investor attention proxies that are an amalgamation of both search-engine measures and social-media measures, rather than just search engine activity (e.g., Google) or social media (e.g., Twitter) alone. This expectation follows from assertions from the field of marketing and professional marketers. While search engine results alone can yield important information, such as the spatial and geographic patterns of attention (Zhang & Tang, 2016), others evidence that search engine marketing and social media marketing work best regarding promoting attention by being combined in tandem as part of an integrated online activities system (Xiang & Gretzel, 2010; Yang et al., 2016).

We expect that cryptocurrencies will be more sensitive to investor attention as a combination of Google and Twitter intensities than they will be to just Google searches or Twitter tweets alone. Search engine optimization and social media promotion have separate but linking functions. Search engine optimization is about users discovering information, creating awareness. Social media, by contrast, is about established relationships and networks being motivated and expanded. The audiences, actions, and outcomes, vis-à-vis levels of search engine activity versus social media activity, are expected to be very different, but reinforcing each other. Search-engine content attracts viewers that follow, comment, and share; thereby increasing, in the longer term, social engagement. And, in turn, social-media engagement, particularly by influential tweeters, or bloggers, increases search engine activity. Social media content stirs short-term emotional responses and animal spirits, accelerating trending topics. In contrast, search engine users are typically research seeking. Although growing a following takes time, social media posts appear instantly, with results often happening within moments. In contrast, search engine activity, typically take days to get indexed and ranked. Social media, therefore, provides a vehicle for much faster attention expansion. This is especially true, of course, for content that ‘goes viral.’

Research in cryptocurrency has expanded enormously in recent years (Conlon & McGee, 2020; Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Eross, Frank, Urquhart, & Wolfe, 2019; Katsiampa, 2019; Katsiampa, Corbet, and Lucey, 2019a, 2019b; Kyriazis, Papadamou, & Corbet, 2020; Mensi, Ur Rehman, Maitra, Al-Yahyaee, & Sensoy, 2020). Additionally, finance scholars have shown considerable recent interest in investor attention (Cheng et al., 2021; Gao & Lin, 2015; Goodell and Huyn, 2020; Guo et al., 2015; Gupta-Mukherjee and Pareek, 2016; Huang, Huang, & Lin, 2019; Hu et al., 2021; Ibikunle, McGroarty, and Rzayev, 2020; Li et al., 2019; Rakowski, Shirley, and Stark, 2018; Zhaunerchyk, Haghighi, & Oliver, 2020). Joining these two streams, a number of researchers have investigated the role of investor attention on cryptocurrencies using Google Trends as a proxy for investor attention (Dastgir et al., 2019; Ibikunle, McGroarty, and Rzayev, 2020; Urquhart, 2018). However, recently, Shen et al. (2019) posit, alternatively, that the volume of Twitter tweets of respective cryptocurrencies is a better proxy of investor attention. Shen et al. (2019) reason that a well-informed investor with rich knowledge of cryptocurrencies prefers to search related information on Twitter instead of Google, as people comment on news posts related to cryptocurrencies or predict the future price of cryptocurrencies via tweets on Twitter. Of course, the question we pose in this study is “What about a blend of search intensity (e.g., Google) and social-media intensity (Twitter) rather than just one form alone?” There is a need for further research to consider how cryptocurrencies comparatively react to differing forms of investor attention. This need extends to considering the best form of modelling investor attention for all financial contexts.

While studies alternatively proxy investor attention as either intensity of Twitter tweets or the intensity of Google searches (Google Trends), there has been little investigation of how Twitter and Google might differ as proxies of investor attention, especially in a cryptocurrency context. Further, cryptocurrencies, because of their know sensitivity to investor attention and investor sentiment (Guégan & Renault, 2021; Naeem, Mbarki, & Shahzad, 2021) are an ideal asset class to conduct this investigation.[1]

Additionally, our motivation for a comprehensive examination of the dynamics of the causality between cryptocurrencies and investor attention is enhanced by existing literature revealing the causal relationship between cryptocurrencies, especially bitcoin in particular, and investor attention through different test methodologies. Urquhart (2018) employs VAR regression, while Shen et al. (2019) utilize linear and nonlinear causality testing. Zhang & Wang, 2020 use quantile regression, and Dastgir et al. (2019) employ copula-based Granger causality testing. However, there remains a need to consider the heterogeneity caused by multiple time scales and the complexity of the cryptocurrency market; as well as a need to expand the investigation of the bi-directional causalities of cryptocurrencies and investor attention to a much larger range of currencies.

Our results indicate a preponderance of bidirectional Granger causality between investor attention and the great majority of cryptocurrencies, with the impact of Twitter on cryptocurrencies being somewhat shorter term. We provide details for the 27

[1] Reboredo & Ugolini, 2018 find that Twitter has little impact on renewable energy companies.

cryptocurrencies regarding the nature of causality (direction, frequency) for both Twitter and Google, along with various combinations of these two measures of investor attention. Most significantly for future research on all types of impact of investor attention, we find that the bi-directional causality of investor attention is greatest, for weightings of Google and Twitter, rather than either alone.

Additional testing with the spillover method of Diebold and Yilmaz (2012), confirms that as a proxy of investor attention, simple equal weightings of normalized Twitter and Google are economically more significant proxies for investor attention than either Twitter or Google used separately. Given recent interest in the impact of investor attention on investment returns, this study on the bi-directional causality of investor attention with 27 cryptocurrencies, comparing measures of investor attention will be of great interest, and has implications for future research on the impact of investor attention on all types of financial contexts.

2. Methodology and data

Given the heterogeneity caused by multiple time scales and the complexity of the cryptocurrency market, we choose a nonparametric wavelet-based Granger causality test (NWGC), as developed by Chen, Bressler, and Ding (2006); Dhamala, Rangarajan, and Ding (2008b); and Torun, Chang, and Chou (2020) to further examine the causal relationship between cryptocurrency and investor concerns (see also Diks & Panchenko, 2006; Omane-Adjepong & Alagidede, 2019).

While there have been a number of investigations of cryptocurrencies using wavelet coherence analysis (e.g., Goodell & Goutte, 2021a; Goodell & Goutte, 2021b), the NWGC is a less-discovered extension of such analysis, allowing for investigation of causalities. This method provides a solution with concurrent multiple time scales, something conventional Granger causality test cannot do. NWGC has two main advantages. First, providing time and frequency representations of the data, NWGC analysis obtains more information about the evolution of the data. As an extension of Granger causality testing based on wavelet analysis, NWGC is suitable for deriving information from multiple time scales. Second, NWGC does not require any autoregressive model; thereby overcoming difficulties inherent with inaccurate model parameters.

Granger (1969) proposes a concept of causality, applying it to linear time series modelling. If time series y_t contains past information that helps predict time series x_t, and this information is not contained in other series used in the prediction, then y_t is said to cause x_t. Consider the univariate and bivariate autoregressive models of a stationary time series x_t and y_t as follows:

$$x_t = \sum_{j=1}^{\infty} a_{1,j}x_{t-j} + \varepsilon_{1,t} \tag{1a}$$

$$y_t = \sum_{j=1}^{\infty} b_{1,j}x_{t-j} + \varepsilon_{1,t} \tag{1b}$$

$$x_t = \sum_{j=1}^{\infty} a_{2,j}x_{t-j} + \sum_{j=1}^{\infty} c_{2,j}y_{t-j} + \varepsilon_{2,t} \tag{1c}$$

$$y_t = \sum_{j=1}^{\infty} b_{2,j}x_{t-j} + \sum_{j=1}^{\infty} d_{2,j}y_{t-j} + \varepsilon_{2,t} \tag{1d}$$

where ε, ε are the prediction errors; a, b is the coefficients between the variables and subscript j represents time lags. If $var(\varepsilon_{2,t}) < var(\varepsilon_{1,t})$, meaning the bivariate model outperforms the univariate one, y_t is said to have a causal effect on x_t in the time-domain. It can be measured as:

$$T_{y\rightarrow x} = ln\left(\frac{var(\varepsilon_{1,t})}{var(\varepsilon_{2,t})}\right) \tag{2}$$

Since financial time series often show strong oscillations, time-domain Granger causality is extended to the frequency-domain Granger causality. Geweke (1982) proposes the spectral decomposition of Granger causality as a function:

$$G_{y\rightarrow x}\left(f\right) = ln\left(\frac{S_{xx}(f)}{S_{xx}(f) - \left(\Sigma_{yy} - \frac{\Sigma_{xy}^2}{\Sigma_{xx}}\right)\left|H_{xy}(f)\right|^2}\right) \tag{3}$$

where $S(f)$ is the spectrum density matrix at frequency f; Σ is the error covariance matrix; $H(f)$ is a spectral transfer function matrix. The spectrum density matrix is defined as $S(f) = H(f)\Sigma H^*(f)$. Here, * is the complex conjugate.

Regarding autoregressive modelling, the parametric approach may produce erroneous results when the autoregressive system equations are not truncated to appropriate model orders. However, obtaining estimations of the spectral transfer function matrix $H(f)$ and the error covariance matrix Σ from Fourier or Wavelet transformations, the nonparametric Granger causality approach solves this problem. The framework of NWGC combines the spectral decomposition of Granger causality with both wavelet analysis and Wilson-Burg factorization. Being provided with the time-frequency representation of the signal, the wavelet transform can be used to analyze non-stationary and non-linear data (Benhmad, 2012). The spectral matrix is quantified by a wavelet transformation of a time series as

$S_{ab} = W_{x_a}(t,f)W^*_{x_b}(t,f)$, where $a = 1, 2$; $b = 1, 2$. The continuous mother wavelet transformation $Wx(t, f)$ is defined by the mother wavelet function $\Psi(\phi)$:

$$W_x(t,s) = |s|^{1/2} \int_{-\infty}^{\infty} x(\phi)\Psi^*\left(\frac{\phi - t}{s}\right)d\phi \tag{4}$$

where * is the complex conjugate. The scale parameter s is related to frequency f. The time-frequency representation of the signal is constructed by varying the scale parameter s and translating along with time t. Following Dhamala, Rangarajan, & Ding, 2008a and Dhamala et al., 2008b, a plane wave modulated by a Gaussian envelop (Morlet wavelet) is chosen as the wavelet function in this paper: $\Psi^*(\phi) = \pi^{-1/4}e^{i\omega\phi}e^{-\phi^2/2}$, and $\omega \geq 6$. The Gaussian envelop $e^{-\phi^2/2}$ localizes the wavelet in time, and ω determines the time or frequency resolution. The scale parameter s is equal to the frequency f approximately. Besides, higher values of ω provide better ratio or frequency resolution, but perform poorer in time resolution. Dhamala et al. (2008b) use Wilson-Burg matrix factorization theorem (Wilson, 1972, 1978) to factorize the spectral density matrix $S(f)$ into a unique minimum-phase functions:

$$S = \psi\psi^* \tag{5}$$

where * is the complex conjugate. ψ is the minimum-phase spectral density matrix factor with $\psi^*(e^{if}) = \sum_{m=0}^{\infty} A_m e^{imf}$, where $A_m = \frac{1}{2\pi}\int_{-\pi}^{\pi} \psi(e^{if})e^{-imf}df$. Here, $\psi(0) = A_0$. The error covariance matrix can be defined as:

$$\Sigma = A_0 A_0^T \tag{6}$$

where A_0^T is the transposition matrix of A_0. After this, Eq. (5) can be rewritten $S = \psi A_0^{-1} A_0 A_0^T A_0^{-T} \psi^*$. Comparing with the spectrum density matrix $S = H\Sigma H = \psi\psi^*$, the transfer function is written as:

$$H = \psi A_0^{-1} \tag{7}$$

Spectral matrix factorization is the key step in the novel non-parametric wavelet Granger causality because it provides H and Σ, which can obtain from the parametric modelling, but cannot obtain from the traditional non-parametric spectral analysis. Compared with alternative spectral factorization algorithms, outstanding numerical efficiency is the main reason to choose the Wilson-Burg factorization method. At each iteration, this algorithm only uses convolutions and deconvolutions, thus avoiding the matrix inversion step. In addition, NWGC does not require assumptions about the order of the autoregressive model; thereby avoiding spurious causality caused by mis-specified errors.

Following Detto et al. (2012), the null hypothesis of no causal influence between time series can be tested through the so-called iterative amplitude adjusted Fourier transform (IAAFT) of Schreiber and Schmitz (2000). Based on synthesizing time series which is the same probability density function and linear correlation structure with the original time series, IAAFT deconstructs any other forms of coupling or nonlinear correlation structures.

In addition to examining the Twitter and Google Trends alone as respective proxies for investor attention, we extend our analysis to include several different weighted combinations of Twitter and Google. We construct three attention proxies (IA_i), which are composed of normalizing the values of Twitter and Google Trends ([−1, 1]) (*T_norm* and *G_norm*), and then employ different strategies as follows:

$$IA_i = w_1 {}^* T_{norm} + w_2 {}^* G_{norm} \tag{8}$$

where, $i = EW, RP, Dynamic$ denotes the methods employed 1/N, risk-parity and dynamically constructed risk-parity strategy, respectively.

We include an equal weighted proxy (IA_{EW}) employed a 1/N strategy, which constructing IA_{EW} as Eq. (8) and the weights of *T_norm* and *G_norm* are as follows:

$$w_1 = w_2 = 0.5 \tag{9}$$

We also employ a risk-parity strategy to construct a proxy for investor attention (IA_{RP}) that satisfying Eq. (8), and the weights are decided by the equation:

$$w_{1,2} = \frac{1/\sigma^2}{\sum_{i=1}^{N} 1/\sigma^2} \tag{10}$$

where, σ^2 denotes the variance respectively of *T_norm* or *G_norm*. We calculate the variance based on the whole sample period.

We also employ a dynamically constructed risk-parity strategy to construct a new proxy investor attention ($IA_{Dynamic}$). After normalizing the values of Twitter and Google Trends ([−1, 1]) (*T_norm* and *G_norm*), we construct $IA_{Dynamic}$ rely on Eq. (8) and Eq. (10). The different between IA_{RP} and $IA_{Dynamic}$ is the calculation of the weights. We dynamically calculate the variance σ^2 based on the past 20 trading days. If the variance of the past 20 trading days is 0, which happens rarely, we assume that the weights of the variable are defined as 1, and the weight of another indicator is 0.

We obtain Twitter data regarding 27 cryptocurrencies from https://bitinfocharts.com/.[2] This data captures the number of times each cryptocurrency is tweeted (e.g., 'Bitcoin', 'Ethereum' etc.). Since Google Trends does not report daily data, we first obtain weekly data over the entire sample. We then calculate a weekly time-varying multiplier to obtain daily data. The Google trends data is obtained by a Python crawler.

We download historical return data for each cryptocurrency from https://coinmarketcap.com/and calculate logarithmic returns via the daily close price data. Table 1 reports the types, sample periods, and descriptive properties of the return series of the 27 cryptocurrencies used in this study. Table 2 provides descriptive statistics for investor attention (Panel A: Twitter; Panel B: Google Trends) toward respective cryptocurrencies. The end of the time series is 2020/5/31. The volume of tweets, intensity of Google searches, and returns of each cryptocurrency have non-symmetric and leptokurtic non-normal distributions.

3. Empirical results

Table 3 reports detailed results of NWGC testing separately for each cryptocurrency, with Table 4 reporting aggregate results. Tables 3 and 4 are both separated into panels according to differing proxies of investor attention. Panel 1 reports Twitter; Panel 2 uses Google Trends; Panel 3 uses an equal weighting of Twitter and Google Trends; Panel 4 uses a static risk-parity-derived weighting of Twitter and Google, while Panel 5 uses a dynamic weighting.

Table 3 displays the directions of causal relationships between levels of investor attention and cryptocurrency returns. The values reported in Table 3 reflect changing the scale parameter s ($s \approx f$) and translating along time t, so that we obtain the time-frequency representation of the data. In the model settings, the reciprocal of a given frequency denotes the cycle length, which means the trading days in multi-time series. Consequently, frequency has another meaning in multi-time series, which is cycles per trading days. As a result, we can display and analyze the results of Granger causality in the frequency domain from the perspective of the time series, making the results more intuitive; as well as more comprehensive.

In examining Table 3, when there are two values of frequencies, or a cycle length denoted with a hyphen, this indicates that there is a Granger causality between the frequency or trading days between the two values. When values for frequencies are separated by commas, it denotes a Granger causality for those particular frequencies. Up (down) arrows mean more (less than the value of this frequency or cycle length).

Examining Tables 3 and 4, it is seen that bi-directional causality is the most, in terms of number of cryptocurrencies, for our equal-weighted and risk-parity weighted proxies (22, or 81.5%, of the 27 cryptocurrencies). Those cryptocurrencies not manifesting bi-directional causality generally demonstrate some form of uni-directional causality. An exception is Theta, which uniquely manifests no causality relationships with any of the investor-attention proxies. For Google Trends without any weighting with Twitter, the cryptocurrencies Dash, Ontology, and Zilliqa, in addition to Theta, also have no causal relationships with any investor attention proxies. Overall, Google has the least number of cryptocurrencies manifesting any causal relationship, while Twitter has the least number of cryptocurrencies manifesting bi-directional causality.

Additionally, employing NWGC testing, we obtain the frequencies of respective Granger causalities. Frequency represents the cycle per trading day of the cryptocurrency. And the cycle length, as well as the trading days, are defined as the reciprocal of a given frequency. Table 3 reports these frequencies by cryptocurrency. Considering the bidirectional causality or the unidirectional causality, we find that the frequency that Granger causality occurs for different cryptocurrencies varies considerably.

Considering 20 trading days as a boundary, we define a period shorter (longer) than 20 trading days as a short-term (long-term) cycle. Table 5 summarizes the results of what percentages of causality are short-term (as opposed to long-term) for 27 cryptocurrencies. Overall, Twitter has the highest percentage of its causalities for the uni-directional case of investor attention impacting returns being short-term (whether part of a bi-directional relationship or not) (50.0%). However, the least percentage of short-term relationships for returns impacting investor attention (25.0%). These results suggest the possibility that the argument of Shen et al., 2019, that Twitter is a more effective vehicle for investor attention for cryptocurrencies, may depend on the direction of causality and time horizon. Google has a higher percentage of short-term relationships for the uni-directional case of returns impacting investor attention (31.8%).

However, our equal-weighting of normalized Twitter and Google, has almost the same percentage of cryptocurrencies manifesting short-term unidirectional causality of investor attention on returns (48.0%) as Twitter alone, and almost as much short-term causality (30.4%) as Google for returns impacting investor attention. If researchers are particularly focused on short-term causalities, it appears that using an equal-weighted average of the normalized values of Twitter and Google is likely the optimal proxy for investor attention. Our risk-parity weighted average is also similarly effective: 43.5% short term of IA on R; and 32.0% R on IA. But the risk-weighted averaging displays slightly more bias than the equal-weighted proxy towards returns impacting investor attention rather than investor attention impacting returns. Overall, our results suggest a very simple optimal approach to modelling investor attention: an equal weighting of the normalized values of Twitter and Google. As an overview, and resource for future research, Appendix A displays Granger causality between the NWGC coefficients of the 27 respective cryptocurrencies and cycle lengths for the specific proxy of the equal weighting of Google and Twitter.

Results of NWGC testing indicate a preponderance of bidirectional Granger causality between investor attention and cryptocurrency returns. Our results complement previous research on investor attention and cryptocurrencies (Shen et al., 2019; Zhang & Wang, 2020), as well as previous studies on the impact of social media on assets more generally (Bollen, Mao, & Zeng, 2011; Ding, Zhou, & Li, 2019; Piñeiro-Chousa, López-Cabarcos, Pérez-Pico, & Ribeiro-Navarrete, 2018; Rakowski, Shirley, & Stark, 2019; Zhang,

[2] We obtain data on the number of tweets for 39 cryptocurrencies from https://bitinfocharts.com/. In order to facilitate the research, we eliminated series with too short periods and too many missing data.Therefore, we obtained data on the number of tweets for 27 cryptocurrencies.

Table 1
Descriptive statistics of 27 cryptocurrency returns.

Cryptocurrency	Start Date	Mean	Std.Dev	Skewness	Kurtosis	JB
Beam	2019/7/15	−0.004	0.074	−3.672	41.052	0.001
Binance Coin	2018/1/24	0.000	0.052	−1.428	18.611	0.001
Bitcoin	2017/1/1	0.002	0.045	−0.932	15.622	0.001
Bitcoin Cash	2018/1/8	−0.002	0.067	−0.473	14.865	0.001
Bitcoin SV	2018/12/7	0.001	0.081	2.761	39.087	0.001
Cardano	2018/1/8	−0.002	0.059	−0.618	10.635	0.001
ChainLink	2018/12/7	0.005	0.068	−0.399	20.835	0.001
Cosmos	2019/4/23	−0.001	0.065	−1.504	20.533	0.001
Dash	2017/1/1	0.002	0.064	0.623	11.432	0.001
Dogecoin	2017/1/1	0.003	0.067	0.636	14.120	0.001
EOS	2018/1/8	−0.001	0.064	−0.350	10.963	0.001
Ethereum	2017/1/1	0.004	0.059	−0.453	12.935	0.001
Ethereum Classic	2017/7/29	0.000	0.065	−0.945	12.379	0.001
Litecoin	2017/1/1	0.003	0.063	0.754	14.028	0.001
Monero	2017/4/20	0.002	0.062	−0.047	10.978	0.001
Neo	2018/1/8	−0.001	0.061	−0.477	9.126	0.001
Nuls	2018/12/7	0.000	0.065	−0.822	21.448	0.001
Ontology	2018/12/7	0.000	0.061	−1.252	23.659	0.001
Qtum	2018/1/8	−0.004	0.064	−1.391	15.525	0.001
Stellar Lumens	2018/4/7	−0.001	0.051	−0.313	10.164	0.001
Tezos	2018/4/7	0.000	0.067	−0.998	14.147	0.001
Theta	2018/12/7	0.003	0.068	−1.032	16.535	0.001
TRON	2018/1/8	−0.003	0.063	−0.793	11.392	0.001
Vechain	2018/12/7	0.001	0.059	−1.726	25.166	0.001
XRP	2018/1/8	−0.003	0.053	−0.551	13.267	0.001
Zcash	2017/7/29	0.000	0.060	−0.214	7.147	0.001
Zilliqa	2018/12/7	0.000	0.060	−1.450	17.638	0.001

The end of the time series is 2020/5/31 for both the volume of tweets and all cryptocurrency returns. Due to missing data of the volume of tweets, the data containing 2017/06/24–2017/7/11 and 2018/3/3–2018/4/6 were eliminated. Std.Dev is standard deviation. JB is the Jarque-Bera test.

Fuehres, & Gloor, 2011); and studies focusing on a comparison of Google and Twitter (Zhang, Zhang, Shen, & Zhang, 2018). Our results compare with Philippas, Rjiba, Guesmi, & Goutte, 2019, who find information flows from Twitter and Google have fundamentally different properties. Our results also are consistent with Elshendy, Colladon Andrea, Battistoni, and Gloor (2018), who find Twitter is more impactful for shorter terms, while Google has more influence over longer periods.

However, despite these differences between Twitter and Google we evidence that a simple equal weighting of the normalized values of Twitter and Google provides an improvement to just Twitter or Google alone as a proxy for investor attention with respect to cryptocurrencies, and does better than other, more complex, weightings. Our results are also consistent with what we expect from marketing research that attention is maximized by combination of search-engine and social media attentions.

4. Additional testing: levels of spillover

To further examine whether combinations of search-engine intensity (Google) and social-media intensity (Twitter) are more potent influencers of cryptocurrency investor attention than either Google or Twitter alone, we additionally employ spillover testing. Spillover testing allows us to better compare the intensity of spillover between attention and cryptocurrency return, using various measures.

Following a number of recent papers (Antonakakis, Chatziantoniou, and Filis, 2014; Corbet et al., 2021; Corbet, Goodell, & Günay, 2020) we employ the procedure of Diebold and Yilmaz (2012). Here, we use the Akaike information criterion to determine the order of the vector autoregressive model and for the forecast horizons we choose 10.[3] Table 6 reports the full-sample spillover table between the 27 cryptocurrencies and their corresponding Twitter and Google trends.[4] The results show that the total spillover index is not high in most cases, ranging from 0.98% (Theta) to 30.86% (ChainLink). Table 6 indicates a significant spillover effect between most cryptocurrency returns and both Twitter and Google Trends. For instance, for ChainLink, Twitter and Google Trends have 12.35% and 8.13% spillover effects on return, respectively. And, from the opposite direction, returns explain about 12.57% and 10.87% of Twitter and Google Trends.

Interestingly, we observe that the signs of net spillover of respectively Twitter and Google Trends to cryptocurrencies tend to tend to manifest in opposite directions. Therefore, we estimate the spillover table again using a 200-day rolling sample to address this phenomenon. Fig. 1 reports the rolling-sample net spillovers in each market for 27 cryptocurrencies. The rolling-sample net spillovers of various markets exhibited relatively strong volatility over time, mainly concentrated in the range of −40%–40%. Regardless of whether the sign of the cryptocurrency's return is positive or negative, its corresponding Twitter and Google Trends are generally opposite. Spillovers between the two attention measures confirm that the attention performance of search-engine and social-media are different and complementary.

[3] Diebold and Yilmaz (2012) show that the method is not sensitive to the order of the model and the forecast horizons.

[4] To improve calculation accuracy, we use Twitter and Google Trends normalized to [-1, 1].

Table 2
Descriptive statistics of investor attention by respective cryptocurrency.

Panel A: Twitter						
Cryptocurrency	Start Date	Mean	Std.Dev	Skewness	Kurtosis	JB
Beam	2019/7/15	43.075	26.018	2.216	10.728	0.001
Binance Coin	2018/1/24	44.908	42.115	2.433	14.214	0.001
Bitcoin	2017/1/1	36206.159	22159.360	1.573	5.346	0.001
Bitcoin Cash	2018/1/8	825.987	664.242	2.429	11.471	0.001
Bitcoin SV	2018/12/7	185.437	119.469	2.928	15.445	0.001
Cardano	2018/1/8	542.270	252.490	2.969	18.845	0.001
ChainLink	2018/12/7	386.467	290.286	1.540	7.183	0.001
Cosmos	2019/4/23	283.993	140.303	6.684	77.841	0.001
Dash	2017/1/1	1431.589	2762.042	7.557	87.392	0.001
Dogecoin	2017/1/1	470.683	352.537	2.550	9.872	0.001
EOS	2018/1/8	1322.641	744.950	2.218	13.625	0.001
Ethereum	2017/1/1	9713.834	7623.833	1.158	3.821	0.001
Ethereum Classic	2017/7/29	160.436	152.520	3.986	29.112	0.001
Litecoin	2017/1/1	2059.175	2312.733	4.989	46.474	0.001
Monero	2017/4/20	488.763	334.233	3.609	30.665	0.001
Neo	2018/1/8	1515.856	3869.948	13.296	231.392	0.001
Cryptocurrency	Start Date	Mean	Std.Dev	Skewness	Kurtosis	JB
Nuls	2018/12/7	49.898	103.395	7.266	83.022	0.001
Ontology	2018/12/7	44.862	34.822	3.556	23.470	0.001
Qtum	2018/1/8	111.542	140.224	5.413	46.226	0.001
Stellar Lumens	2018/4/7	31.454	44.711	3.844	23.873	0.001
Tezos	2018/4/7	394.237	330.986	3.165	19.983	0.001
Theta	2018/12/7	97.946	500.833	17.691	358.227	0.001
TRON	2018/1/8	9485.481	20544.300	10.890	156.677	0.001
Vechain	2018/12/7	244.325	211.715	3.503	22.212	0.001
XRP	2018/1/8	5562.435	2184.201	1.850	8.796	0.001
Zcash	2017/7/29	245.409	188.738	2.785	14.975	0.001
Zilliqa	2018/12/7	237.904	1810.028	13.074	183.175	0.001
Panel B: Google Trends						
Cryptocurrency	Start Date	Mean	Std.Dev	Skewness	Kurtosis	JB
Beam	2019/7/15	56.292	5.327	0.301	4.357	0.001
Binance Coin	2018/1/24	2.032	2.782	3.621	21.922	0.001
Bitcoin	2017/1/1	12.079	15.191	5.275	39.951	0.001
Bitcoin Cash	2018/1/8	2.581	1.856	3.270	17.658	0.001
Bitcoin SV	2018/12/7	6.931	12.509	5.804	48.455	0.001
Cryptocurrency	Start Date	Mean	Std.Dev	Skewness	Kurtosis	JB
Cardano	2018/1/8	7.014	6.671	3.969	24.024	0.001
ChainLink	2018/12/7	29.945	22.520	2.642	21.164	0.001
Cosmos	2019/4/23	65.634	15.674	1.101	5.413	0.001
Dash	2017/1/1	53.429	7.669	5.576	65.302	0.001
Dogecoin	2017/1/1	11.823	16.315	4.902	35.313	0.001
EOS	2018/1/8	63.755	11.723	1.578	9.529	0.001
Ethereum	2017/1/1	16.021	20.456	2.846	12.121	0.001
Ethereum Classic	2017/7/29	11.844	14.921	6.348	68.364	0.001
Litecoin	2017/1/1	4.051	10.697	11.190	185.839	0.001
Monero	2017/4/20	12.047	18.449	3.733	18.746	0.001
Neo	2018/1/8	25.254	4.742	2.823	20.193	0.001
Nuls	2018/12/7	5.179	6.075	1.199	4.934	0.001
Ontology	2018/12/7	49.441	22.651	0.600	3.496	0.001
Qtum	2018/1/8	1.837	3.643	4.265	26.902	0.001
Stellar Lumens	2018/4/7	15.903	3.789	0.786	5.295	0.001
Tezos	2018/4/7	16.575	16.455	2.693	14.736	0.001
Theta	2018/12/7	48.169	14.518	1.960	17.017	0.001
TRON	2018/1/8	14.537	8.165	5.401	44.627	0.001
Vechain	2018/12/7	8.596	5.907	3.326	31.845	0.001
Cryptocurrency	Start Date	Mean	Std.Dev	Skewness	Kurtosis	JB
XRP	2018/1/8	9.664	7.322	5.646	46.468	0.001
Zcash	2017/7/29	12.958	17.303	2.673	10.748	0.001
Zilliqa	2018/12/7	3.927	5.632	2.023	8.551	0.001

This table presents descriptive statistics for investor attention (Panel A: Twitter; Panel B: Google Trends) toward respective cryptocurrencies. The end of the time series is 2020/5/31 for both the volume of tweets and all cryptocurrency returns. Due to missing data of the volume of tweets, the data containing 2017/06/24–2017/7/11 and 2018/3/3–2018/4/6 were removed. Std.Dev is standard deviation. JB is the Jarque-Bera test.

Table 3
Detailed description of causalities.

Panel 1: Twitter					
Cryptocurrency	Causal relationship	***IA → R***		***R → IA***	
		Frequency (cycles per trading day)	Cycle length (trading days)	Frequency (cycles per trading day)	Cycle length (trading days)
Beam	*IA → R*	0.25	4		
Binance Coin	*IA ↔ R*	0.05–0.08	12–20	0.05, 0.25	20, 4
Bitcoin	*IA ↔ R*	0.04–0.05	20–25	0.02	50
Bitcoin Cash	*IA ↔ R*	0.03↓, 0.05–0.09, 0.11–0.16	32↑, 11–20, 6–9	0.04, 0.13–0.14	25, 7–8
Bitcoin SV	*R → IA*			0.07–0.09, 0.13–0.17, 0.29↑	11–14, 6–8, 4↓
Cardano	*R → IA*			0.02–0.03, 0.05, 0.09–0.13	33–50, 20, 8–11
ChainLink	*IA ↔ R*	0.07–0.11, 0.39	9–14, 3	0.05–0.06, 0.44	16–20, 2
Cosmos	*IA ↔ R*	0.11, 0.40	9, 3	0.01–0.03, 0.17–0.20	33–100, 5–6
Dash	*IA → R*	0.07–0.09, 0.14–0.18	11–14, 5–7		
Dogecoin	*IA ↔ R*	0.35	3	0.05–0.06, 0.08–0.11, 0.25↑	16–20, 9–12, 4↓
EOS	*IA ↔ R*	0.01–0.03, 0.06, 0.35	33–100, 16, 3	0.07	14
Ethereum	*R → IA*			0.07–0.17, 0.31	6–14, 3
Ethereum Classic	*IA ↔ R*	0.07–0.08, 0.17–0.25	12–14, 4–6	0.01–0.02, 0.05–0.07	50–100, 14–20
Litecoin	*IA ↔ R*	0.05, 0.09–0.35	20, 3–11	0.01, 0.04, 0.12–0.13, 0.17↑	100, 25, 8, 6↓
Monero	*IA ↔ R*	0.34↑	3↓	0.03–0.04, 0.06–0.13, 0.28–0.31	25–32, 8–16, 3–4
Neo	*IA ↔ R*	0.21–0.25	4–5	0.06–0.07	14–16
Nuls	*R → IA*			0.04–0.05, 0.08	20–25, 12
Ontology	*IA ↔ R*	0.01↓, 0.21–0.34	100↑, 3–5	0.01↓	100↑
Qtum	*IA ↔ R*	0.08–0.12	8–12	0.19↑	5↓
Stellar Lumens	*IA ↔ R*	0.05–0.06, 0.33↑	16–20, 3↓	0.01↓, 0.04–0.05, 0.10–0.12	100↑, 20–25, 8–10
Tezos	*IA ↔ R*	0.28	4	0.03, 0.23↑	33, 4↓
Theta	*NO*				
TRON	*IA ↔ R*	0.08–0.09	11–12	0.01, 0.16–0.38	3–6
Vechain	*IA ↔ R*	0.05, 0.13–0.14	20, 7–8	0.01↓, 0.07–0.08, 0.11, 0.47	100↑, 12–14, 9, 2
XRP	*IA ↔ R*	0.01–0.07, 0.11–0.32	14–100, 3–9	0.05, 0.15–0.16	20, 6–7
Zcash	*IA ↔ R*	0.05–0.06, 0.17–0.36	16–20, 3–6	0.05, 0.11–0.15, 0.36	20, 7–9, 3
Zilliqa	*IA ↔ R*	0,01, 0.06–0.07, 0.09–0.11, 0.17	100, 14–16, 9–11, 6	0.03–0.04, 0.21↑	25–33, 5↓
Panel 2: Google Trends					
Cryptocurrency	Causality	***IA → R***		***R → IA***	
		Frequency (cycle per trading day)	Cycle Length (trading days)	Frequency (cycle per trading day)	Cycle Length (trading days)
Beam	*IA ↔ R*	0.01↓	100↑	0.01↓, 0.05, 0.07–0.09, 0.17–0.38	100↑, 20, 11–14, 3–6
Binance Coin	*IA ↔ R*	0.01–0.02, 0.04, 0.09–0.11	50–100, 25, 9–11	0.06, 0.15↑	16, 7↓
Bitcoin	*IA ↔ R*	0.03–0.05, 0.10, 0.21–0.40	20–33, 10, 3–5	0.01–0.02, 0.09–0.12	50–100, 8–11
Bitcoin Cash	*IA ↔ R*	0.03↓, 0.05–0.15, 0.21–0.27, 0.45	33↑, 7–20, 4–5, 2	0.11, 0.25–0.32	9, 3–4
Bitcoin SV	*IA ↔ R*	0.06–0.08, 0.13–0.16, 0.30	12–16, 6–8, 3	0.01, 0.12↑	100, 8↓
Cardano	*IA ↔ R*	0.01–0.02, 0.05, 0.13–0.26, 0.50	50–100, 20, 4–8, 2	0.04, 0.13–0.23, 0.50	25, 4–8, 2
ChainLink	*IA ↔ R*	0.09–0.13, 0.36	8–11, 3	0.02–0.03, 0.05–0.06, 0.10, 0.46	33–50, 16–20, 10, 2
Cosmos	*IA ↔ R*	0.18–0.23	4–5	0.27, 0.50	4, 2
Dash	*No*				
Dogecoin	*IA ↔ R*	0.02, 0.06, 0.11, 0.17↑	50, 16, 9, 6↓	0.05, 0.09–0.11, 0.19↑	20, 9–11, 5↓
EOS	*IA → R*	0.01, 0.10–0.11, 0.17–0.26	100, 9–10, 4–6	–	–
Ethereum	*IA ↔ R*	0.06, 0.11–0.12	16, 8–9	0.05–0.06, 0.09–0.11, 0.14–0.16, 0.39↑	16–20, 9–11, 6–7, 3↓
Ethereum Classic	*IA ↔ R*	0.01↓, 0.07	100↑, 14	0.01↓, 0.10	100↑, 10
Litecoin	*IA ↔ R*	0.01↓, 0.05, 0.10–0.12, 0.36	100↑, 20, 8–10, 3	0.01↓, 0.09, 0.11–0.15, 0.27↑	100↑, 11, 7–9, 4↓
Monero	*IA ↔ R*	0.10–0.16	6–10	0.01↓, 0.05–0.09, 0.12↑	100↑, 11–20, 8↓
Neo	*IA ↔ R*	0.01, 0.15–0.16	100, 6–7	0.12, 0.29↑	8, 4↓
Nuls		0.08, 017, 0.28, 0.48	12, 6, 4, 2	0.03	33

(*continued on next page*)

Table 3 (*continued*)

Panel 1: Twitter					
Cryptocurrency	Causal relationship	***IA* → *R***		***R* → *IA***	
		Frequency (cycles per trading day)	Cycle length (trading days)	Frequency (cycles per trading day)	Cycle length (trading days)
	IA ↔ *R*				
Ontology	*NO*				
Qtum	*IA* ↔ *R*	0.12↑	8↓	0.04–0.05, 0.07, 0.10–0.17, 0.50	20–25, 14, 6–10, 2
Stellar Lumens	*IA* ↔ *R*	0.01, 0.10–0.13	100, 8–10	0.01↓, 0.05–0.08, 0.11–0.14, 0.20–0.26	100↑, 12–20, 7–9, 4–5
Tezos	*R* → *IA*			0.19, 0.30↑	5, 3↓
Theta	*NO*				
TRON	*IA* ↔ *R*	0.01, 0.04–0.10, 0.14↑	100, 10–25, 7↓	0.02–0.03	33–50
Vechain	*IA* ↔ *R*	0.01↓, 0.12–0.16	100↑, 6–8	0.01↓, 0.07, 0.10–0.12, 0.17	100↑, 14, 8–10, 6
XRP	*IA* ↔ *R*	0.01–0.03, 0.05–0.07, 0.09–0.15, 0.32↑	33–100, 14–20, 7–11, 3↓	0.17–0.30	3–6
Zcash	*IA* ↔ *R*	0.25↑	4↓	0.06–0.07, 0.15–0.39	14–16, 3–7
Zilliqa	*NO*				
Panel 3: Equal weighted					
Cryptocurrency	Causality	***IA* → *R***		***R* → *IA***	
		Frequency (cycle per trading day)	Cycle Length (trading days)	Frequency (cycle per trading day)	Cycle Length (trading days)
Beam	*IA* ↔ *R*	0.01↓	100↑	0.05, 0.18–0.38	20, 3–5
Binance Coin	*IA* ↔ *R*	0.01–0.02, 0.07–0.10	50–100, 10–14	0.11, 0.15–0.28, 0.45	9, 4–7, 2
Bitcoin	*IA* ↔ *R*	0.04–0.06, 0.10–0.11, 0.23–0.38	16–25, 9–10, 3–4	0.01–0.02, 0.10, 0.12	50–100, 10, 8
Bitcoin Cash	*IA* ↔ *R*	0.03↓, 0.05–0.15	33↑, 7–20	0.01↓, 0.13–0.14, 0.34	100↑, 7–8, 3
Bitcoin SV	*IA* ↔ *R*	0.06, 0.13–0.14	16, 7–8	0.12–0.17, 0.22↑	6–8, 4↓
Cardano	*IA* ↔ *R*	0.01, 0.15–0.18	100, 5–7	0.09–0.10, 0.22, 0.47	10–11, 4, 2
ChainLink	*IA* ↔ *R*	0.08–0.11, 0.35↑	9–12, 3↓	0.03, 0.05–0.07, 0.40↑	33, 14–20, 3↓
Cosmos	*IA* ↔ *R*	0.18↑	5↓	0.28↑	4↓
Dash	*IA* ↔ *R*	0.16	6	0.36	3
Dogecoin	*IA* ↔ *R*	0.18↑	5↓	0.02↓, 0.05–0.06, 0.09–0.11, 0.21↑	50↑, 16–20, 9–11, 5↓
EOS	*IA* → *R*	0.01, 0.07, 0.17–0.20	100, 14, 5–6		
Ethereum	*R* → *IA*			0.05–0.06, 0.08–0.16, 0.24	16–20, 6–12, 4
Ethereum Classic	*IA* ↔ *R*	0.02↓, 0.07–0.08, 0.17–0.26	50↑, 12–14, 4–6	0.05, 0.10, 0.16	20, 10, 6
Litecoin	*IA* ↔ *R*	0.03, 0.05, 0.09–0.11, 0.14–0.16, 0.27–0.35	33, 20, 9–11, 6–7, 3–4	0.01↓, 0.11–0.14, 0.18↑	100↑, 7–9, 5↓
Monero	*IA* ↔ *R*	0.36↑	3↓	0.01, 0.03–0.04, 0.06–0.10, 0.13–0.18, 0.36	100, 25–33, 10–16, 5–8, 3
Neo	*IA* ↔ *R*	0.01, 0.15–0.21, 0.50	100, 5–7, 2	0.06, 0.12, 0.33↑	16, 8, 3↓
Nuls	*IA* → *R*	0.46	2		
Ontology	*IA* ↔ *R*	0.37	3	0.01↓, 0.09–0.14	100↑, 7–11
Qtum	*IA* ↔ *R*	0.11–0.21	5–9	0.04–0.05, 0.07, 0.10, 0.12–0.24, 0.50	20–25, 14, 10, 4–8, 2
Stellar Lumens	*IA* ↔ *R*	0.05–0.07, 0.13	14–20, 8	0.01↓, 0.11–0.14, 0.20–0.26	100↑, 7–9, 4–5
Tezos	*IA* ↔ *R*	0.08–0.11	9–12	0.08–0.13, 0.16–0.20, 0.29↑	8–12, 5–6, 3↓
Theta	*N*0				
TRON	*IA* ↔ *R*	0.01, 0.08–0.10, 0.16↑	100, 10–12, 6↓	0.02, 0.17–0.23	50, 4–6
Vechain	*IA* ↔ *R*	0.01↓, 0.05, 0.12–0.15	100↑, 20, 7–8	0.01↓, 0.07–0.08, 0.11–0.12, 0.19–0.27	100↑, 12–14, 8–9, 4–5
XRP	*IA* ↔ *R*	0.01–0.07, 0.09–0.15, 0.19, 0.34↑	14–100, 7–11, 5, 3↓	0.05, 0.15–0.19	20, 5–7
Zcash	*IA* ↔ *R*	0.27↑	4↓	0.03, 0.11–0.18, 0.34↑	33, 5–9, 3↓
Zilliqa	*IA* → *R*	0.07, 0.10, 0.17	14, 10, 6		
Panel 4: Risk Parity Static Weighted					
Cryptocurrency	Causality	***IA* → *R***		***R* → *IA***	
				Frequency (cycle per trading day)	

(*continued on next page*)

Table 3 (*continued*)

Panel 1: Twitter					
Cryptocurrency	Causal relationship	***IA → R***		***R → IA***	
		Frequency (cycles per trading day)	Cycle length (trading days)	Frequency (cycles per trading day)	Cycle length (trading days)
		Frequency (cycle per trading day)	Cycle Length (trading days)		Cycle Length (trading days)
Beam	*R → IA*	–		0.05, 0.18–0.38	20, 3–5
Binance Coin	*IA ↔ R*	0.01–0.02, 0.07–0.10	50–100, 10–14	0.11, 0.15–0.28, 0.45	10, 4–7, 2
Bitcoin	*IA ↔ R*	0.04–0.06, 0.10, 0.22–0.40	16–25, 10, 3–5	0.09–0.12	8–11
Bitcoin Cash	*IA ↔ R*	0.03↓, 0.05–0.15	33↑, 7–20	0.01↓, 0.13–0.14, 0.32	100↑, 7–8, 3
Bitcoin SV	*IA ↔ R*	0.01↓, 0.06, 0.13–0.14	100↑, 16, 7–8	0.01↓, 0.12–0.16, 0.21↑	100↑, 6–8, 4↓
Cardano	*IA ↔ R*	0.01, 0.15–0.18	100, 5–7	0.03, 0.09–0.10, 0.22, 0.47	33, 10–11, 4, 2
ChainLink	*IA ↔ R*	0.08–0.12, 0.35↑	8–12, 3↓	0.03, 0.05–0.06, 0.45	33, 16–20, 2
Cosmos	*IA ↔ R*	0.37↑	3↓	0.03–0.04, 0.17–0.19, 0.29↑	25–33, 5–6, 3↓
Dash	*IA ↔ R*	0.16	6	0.37	3
Dogecoin	*IA ↔ R*	0.10, 0.17↑	10, 6↓	0.05, 0.09–0.11,0.20↑	20, 9–11, 5↓
EOS	*IA → R*	0.01, 0.07, 0.17–0.20	100, 14, 5–6		
Ethereum	*R → IA*			0.05–0.06, 0.08–0.17, 0,24	16–20, 6–12, 4
Ethereum Classic	*IA ↔ R*	0.01↓, 0.07–0.08, 0.19–0.25	100↑, 12–14, 4–5	0.01↓, 0.05, 0.10, 0.16	100↑, 20, 10, 6
Litecoin	*IA ↔ R*	0.01↓, 0.05, 0.09–0.11, 0.34	100↑, 20, 9–11, 3	0.01↓, 0.09, 0.11–0.15, 0.25↑	100↑, 11, 7–9, 4↓
Monero	*IA ↔ R*	0.34↑	3↓	0.01, 0.03–0.04, 0.06–0.11	100, 25–33, 9–16
Neo	*IA ↔ R*	0.16–0.21	5–6	0.06–0.07, 0.48	14–16, 2
Nuls	*R → IA*			0.04–0.05	20–25
Ontology	*IA ↔ R*	0.01↓, 0.34	100↑, 3	0.01↓, 0.09–0.10, 0.13–0.14	100↑, 10–11, 7–8
Qtum	*IA ↔ R*	0.09–0.12, 0.16–0.20	8–11, 5–6	0.04–0.05, 0.10, 0.13–0.26	20–25, 10, 4–8
Stellar Lumens	*IA ↔ R*	0.05–0.07, 0.13, 0.37	14–20, 8, 3	0.13, 0.21–0.25	8, 4–5
Tezos	*IA ↔ R*	0.09–0.10	10–11	0.08–0.12, 0.17–0.19, 0.29↑	8–12, 5–6, 3↓
Theta	*NO*				
TRON	*IA ↔ R*	0.01, 0.03, 0.08–0.10, 0.19	100, 33, 10–12, 5	0.02, 0.17–0.25	50, 4–6
Vechain	*IA ↔ R*	0.01↓, 0.05, 0.12–0.16	100↑, 20, 6–8	0.01↓, 0.07–0.08, 0.10–0.12, 0.18–0.27	100↑, 12–14, 8–10, 4–5
XRP	*IA ↔ R*	0.01–0.07, 0.09–0.15, 0.18, 0.33↑	14–100, 7–11, 5, 3↓	0.15–0.21, 0.28	5–7, 4
Zcash	*IA ↔ R*	0.16, 0.28↑	6, 4↓	0.11–0.17, 0.36	6–9, 3
Zilliqa	*IA ↔ R*	0.06–0.07, 0.09–0.12, 0.15–0.17	14–16, 8–11, 6–7	0.03–0.04	25–33

Panel 5: Dynamic Weighting					
Cryptocurrency	Causality	***IA → R***		***R → IA***	
		Frequency (cycle per trading day)	Cycle Length (trading days)	Frequency (cycle per trading day)	Cycle Length (trading days)
Beam	*R → IA*			0.01–0.02, 0.05, 0.21	50–100, 20, 5
Binance Coin	*IA ↔ R*	0.06, 0.09, 0.14–0.17, 0.50	20, 11, 6–7, 2	0.14↑	7↓
Bitcoin	*IA ↔ R*	0.03–0.06, 0.11, 0.23–0.40	16–33, 9, 3–4	0.02, 0.05, 0.09–0.12, 0.17, 0.37↑	50, 20, 8–11, 6, 3↓
Bitcoin Cash	*IA ↔ R*	0.01, 0.04–0.09, 0.11–0.13	100, 11–25, 8–9	0.14	7
Bitcoin SV	*IA ↔ R*	0.06–0.08, 0.10–0.11, 0.14	12–16, 9–10, 7	0.10, 0.12, 0.16, 0.23↑	10, 8, 6, 4↓
Cardano	*IA ↔ R*	0.01–0.02, 0.04, 0.25↑	50–100, 25, 4↓	0.11, 0.20↑	9, 5↓
ChainLink	*IA ↔ R*	0.34↑	3↓	0.03, 0.05–0.07, 0.45	33, 14–20, 2
Cosmos	*R → IA*			0.08, 0.30↑	12, 3↓
Dash	*R → IA*			0.02–0.03, 0.12–0.14	33–50, 7–8
Dogecoin	*IA ↔ R*	0.02, 0.10↑	50, 10↓	0.05, 0.09–0.11,0.20↑	20, 9–11, 5↓
EOS	*IA ↔ R*	0.01↓, 0.16–0.20	100↑, 5–6	0.01↓, 0.03, 0.05, 0.25–0.40	100↑, 33, 20, 3–4
Ethereum	*IA ↔ R*	0.21–0.27	4–5	0.01↓, 0.04–0.05, 0.08–0.17	100↑, 20–25, 6–12
Ethereum Classic	*IA ↔ R*	0.01↓, 0.04, 0.07, 0.10, 0.21–0.13	100↑, 25, 14, 10, 4–5	0.01↓, 0.05, 0.16	100↑, 20, 6
Litecoin	*IA ↔ R*	0.03, 0.05–0.06, 0.10–0.12, 0.34	100↑, 16–20, 8–10, 3	0.01↓, 0.09–0.15, 0.25↑	100↑, 7–11, 4↓
Monero	*IA ↔ R*	0.10	10	0.01↓, 0.05, 0.07–0.10, 0.14	100↑, 20, 10–14, 7

(*continued on next page*)

Table 3 (*continued*)

Panel 1: Twitter					
Cryptocurrency	Causal relationship	$IA \to R$		$R \to IA$	
		Frequency (cycles per trading day)	Cycle length (trading days)	Frequency (cycles per trading day)	Cycle length (trading days)
Neo	$IA \to R$	0.24	4		
Nuls	$IA \to R$	0.15	7		
Ontology	$IA \leftrightarrow R$	0.01↓, 0.32	100↑, 3	0.01↓, 0.07–0.08	100↑, 12–14
Qtum	$IA \leftrightarrow R$	0.06–0.08, 0.10–0.13, 0.16, 0.50	12–16, 8–10, 6, 2	0.03–0.05, 0.08–0.10, 0.22↑	20–33, 10–12, 4↓
Stellar Lumens	$IA \leftrightarrow R$	0.01↓, 0.33↑	100↑, 3↓	0.01↓, 0.10–0.15, 0.27–0.31	100↑, 7–10, 3–4
Tezos	$R \to IA$			0.04, 0.07–0.12, 0.17↑	25, 8–14, 6↓
Theta	*NO*				
TRON	$IA \leftrightarrow R$	0.02↓, 0.08–0.10	50↑, 10–12	0.44	2
Vechain	$IA \leftrightarrow R$	0.01↓, 0.13–0.15	100↑, 7–8	0.01↓, 0.11–0.12	100↑, 8–9
XRP	$IA \leftrightarrow R$	0.01, 0.04–0.09, 0.25↑	100, 11–25, 4↓	0.04, 0.10–0.13, 0.27↑	25, 8–10, 4↓
Zcash	$IA \leftrightarrow R$	0.27↑	4↓	0.03, 0.11, 0.14–0.16, 0.23↑	33, 9, 6–7, 4↓
Zilliqa	$IA \leftrightarrow R$	0.01–0.02, 0.35↑	50–100, 3↓	0.03, 0.09–0.12, 0.25↑	33, 8–11, 4↓

Table provides detailed description of directions, frequencies, and cycle lengths for the causality between various proxies of investor attention and respective cryptocurrencies*IA* denotes the respective investor attention proxy, *R* denotes the respective return, $IA \leftrightarrow R$ denotes bidirectional causality, $IA \to R$ denotes unidirectional causality from tweets to return, $R \to IA$ denotes unidirectional causality from return to tweets, *NO* denotes no significant causality. ↑ denotes 'equal and higher than' and ↓ denotes 'equal and lower than' frequency and cycle length.

Table 4
Aggregate summary of causalities.

Investor-attention proxy	cryptocurrencies with causal relationship	$IA \leftrightarrow R$	$IA \to R$	$R \to IA$	No causality
Twitter	26	20 (74.1%)	2 (7.4%)	4 (14.8%)	1 (3.7%)
Google Trends	23	21 (77.8%)	1 (3.7%)	1 (3.7%)	4 (14.8%)
Equal Weighting	26	22 (81.5%)	3 (11.1%)	1 (3.7%)	1 (3.7%)
Risk-parity weighting	26	22 (81.5%)	1 (3.7%)	3 (11.1%)	1 (3.7%)
Dynamic weighting	26	20 (74.1%)	2 (7.4%)	4 (14.8%)	1 (3.7%)

Table describes in aggregate the nature of causalities between several different proxies of investor attention and 28 cryptocurrencies. *IA* denotes investor attention, *R* denotes the returns, $IA \leftrightarrow R$ denotes bidirectional causality, $IA \to R$ denotes unidirectional causality from tweets to return, $R \to IA$ denotes unidirectional causality from return to tweets. Numbers are the number of cryptocurrencies or percentage out of 28.

Table 5
Summary of short-term versus long-term causalities for differing investor attention proxies.

	% causality short-term	
Investor Attention Proxy	$IA \to R$	$R \to IA$
Twitter	50.0%	25.0%
Google	36.4%	31.8%
Equal Weighted	48.0%	30.4%
Risk-Parity Weighted	43.5%	32.0%
Dynamic Weighted	36.4%	25.0%

Short-term (long-term) is defined as a time scale shorter (greater) than 20 trading days. 28 currencies total. *IA* is investor attention, R is cryptocurrency return.

These results are consistent with what our expectations that attention is conveyed best through combination of search engine and social media attentions. Results evidence that researchers ought to construct multi-source proxies of attention that are formed from both search-engine and social-media intensities.

We then further compare directional spillovers from $IA_{Twitter}$, IA_{Google}, IA_{EW}, IA_{RP} $IA_{Dynamic}$ to returns for the 27 cryptocurrencies (Fig. 2).[5] Examining Fig. 2, it is clear that spillover intensity between cryptocurrencies and the three multi-source attention proxies is similar and strikingly more significant than for either single-source attention proxy. The results of spillover analysis suggest that there is economically significantly more spillover between cryptocurrency returns and measures of attention that are a blend of search-engine and social-media measures, rather than either alone.

[5] There are similar results from return to IA_i. To save space, we report the directional spillovers from IA_i to returns.

Table 6
Full-sample Spillover table, Twitter, Google Trends and Return for 27 Cryptocurrencies.

	Twitter	Google	Return	From Others	Twitter	Google	Return	From Others	Twitter	Google	Return	From Others
	Beam				Binance Coin				Bitcoin			
Twitter	98.20	0.63	1.16	1.80	96.54	0.34	3.11	3.46	78.67	20.79	0.54	21.33
Google	0.55	98.59	0.86	1.41	0.04	96.83	3.13	3.17	31.52	67.82	0.66	32.18
Return	1.26	0.18	98.56	1.44	2.47	1.51	96.02	3.98	0.46	0.71	98.82	1.18
To Others	1.81	0.81	2.03	1.55	2.51	1.85	6.25	3.53	31.99	21.50	1.21	18.23
Net	0.01	−0.60	0.59		−0.95	−1.32	2.27		10.65	−10.68	0.03	
	Bitcoin Cash				Bitcoin SV				Cardano			
Twitter	93.77	4.73	1.50	6.23	78.44	15.39	6.17	21.56	80.91	15.52	3.56	19.09
Google	20.63	74.14	5.23	25.86	13.71	63.19	23.09	36.81	8.05	85.86	6.09	14.14
Return	0.91	4.16	94.93	5.07	4.00	15.57	80.43	19.57	0.79	4.89	94.32	5.68
To Others	21.54	8.89	6.73	12.39	17.71	30.95	29.26	25.98	8.85	20.42	9.65	12.97
Net	15.32	−16.98	1.66		−3.84	−5.86	9.70		−10.24	6.27	3.97	
	ChainLink				Cosmos				Dash			
Twitter	63.83	23.60	12.57	36.17	98.14	1.22	0.63	1.86	97.79	2.02	0.19	2.21
Google	25.06	64.08	10.87	35.92	0.31	99.25	0.44	0.75	2.33	97.46	0.21	2.54
Return	12.35	8.13	79.52	20.48	0.84	0.94	98.22	1.78	0.25	0.08	99.67	0.33
To Others	37.41	31.73	23.44	30.86	1.15	2.17	1.08	1.46	2.58	2.10	0.40	1.69
Net	1.24	−4.19	2.96		−0.71	1.41	−0.70		0.37	−0.43	0.06	
	Dogecoin				EOS				Ethereum			
Twitter	82.95	9.69	7.37	17.05	97.65	1.55	0.81	2.35	93.14	4.67	2.19	6.86
Google	7.30	76.91	15.79	23.09	1.86	96.07	2.07	3.93	2.82	88.85	8.33	11.15
Return	4.15	8.13	87.72	12.28	0.95	2.25	96.80	3.20	0.59	0.84	98.57	1.43
To Others	11.45	17.82	23.16	17.47	2.81	3.80	2.88	3.16	3.41	5.51	10.52	6.48
Net	−5.61	−5.27	10.88		0.45	−0.13	−0.32		−3.45	−5.64	9.09	
	Ethereum Classic				Litecoin				Monero			
Twitter	88.67	7.46	3.87	11.33	69.11	28.12	2.78	30.89	91.74	6.74	1.52	8.26
Google	14.42	80.13	5.45	19.87	33.22	59.21	7.57	40.79	5.40	82.89	11.71	17.11
Return	3.22	4.55	92.23	7.77	3.77	4.48	91.75	8.25	0.79	3.26	95.95	4.05
To Others	17.63	12.01	9.32	12.99	36.99	32.60	10.34	26.65	6.20	10.00	13.23	9.81
Net	6.31	−7.86	1.55		6.10	−8.19	2.09		−2.06	−7.11	9.17	
	Twitter	Google	Return	From Others	Twitter	Google	Return	From Others	Twitter	Google	Return	From Others
	Neo				Nuls				Ontology			
Twitter	98.93	0.89	0.19	1.07	97.78	0.22	2.01	2.22	90.89	5.39	3.71	9.11
Google	17.60	80.73	1.67	19.27	0.78	97.74	1.48	2.26	1.33	98.56	0.12	1.44
Return	0.08	0.68	99.24	0.76	1.44	2.09	96.47	3.53	3.02	0.67	96.32	3.68
To Others	17.68	1.57	1.86	7.03	2.22	2.31	3.49	2.67	4.34	6.06	3.83	4.75
Net	16.61	−17.70	1.10		0.00	0.05	−0.05		−4.77	4.62	0.15	
	Qtum				Stellar Lumens				Tezos			
Twitter	95.23	3.42	1.35	4.77	89.31	4.02	6.67	10.69	83.32	7.23	9.45	16.68
Google	3.73	92.13	4.13	7.87	6.54	89.49	3.97	10.51	9.24	83.73	7.03	16.27
Return	0.84	3.26	95.90	4.10	4.04	0.55	95.41	4.59	3.84	3.57	92.60	7.40
To Others	4.58	6.68	5.48	5.58	10.58	4.57	10.64	8.60	13.08	10.80	16.47	13.45
Net	−0.19	−1.18	1.38		−0.11	−5.94	6.05		−3.60	−5.47	9.07	
	Theta				TRON				Vechain			
Twitter	98.45	1.38	0.18	1.55	95.21	4.35	0.44	4.79	80.04	9.43	10.53	19.96
Google	0.46	99.27	0.26	0.73	0.57	97.64	1.79	2.36	14.56	78.48	6.96	21.52
Return	0.38	0.27	99.35	0.65	0.23	1.65	98.12	1.88	7.85	3.74	88.40	11.60
To Others	0.84	1.65	0.44	0.98	0.81	6.00	2.23	3.01	22.41	13.17	17.49	17.69
Net	−0.71	0.92	−0.21		−3.99	3.64	0.35		2.45	−8.35	5.90	
	XRP				Zcash				Zilliqa			
Twitter	80.69	15.84	3.47	19.31	82.30	15.94	1.75	17.70	99.65	0.05	0.30	0.35
Google	25.03	70.15	4.82	29.85	4.71	88.64	6.65	11.36	0.52	98.38	1.10	1.62
Return	4.20	4.99	90.81	9.19	1.72	4.08	94.20	5.80	2.51	0.44	97.05	2.95
To Others	29.22	20.83	8.29	19.45	6.43	20.02	8.41	11.62	3.03	0.49	1.40	1.64
Net	9.91	−9.01	−0.90		−11.26	8.66	2.60		2.68	−1.13	−1.55	

Notes: The total spillover index is bold.

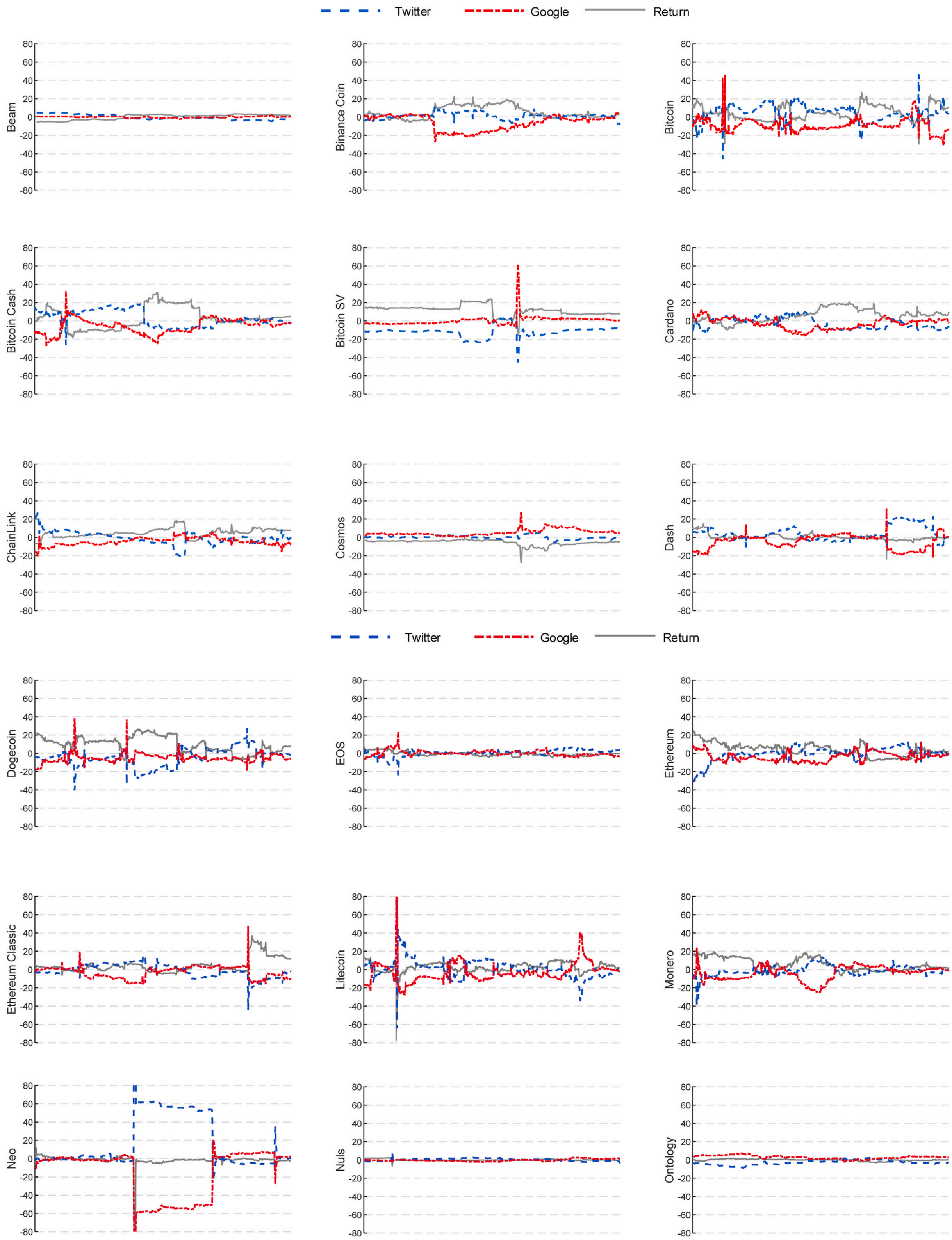


Fig. 1. Rolling-sample net spillovers, twitter, google search and return for 27 cryptocurrencies.

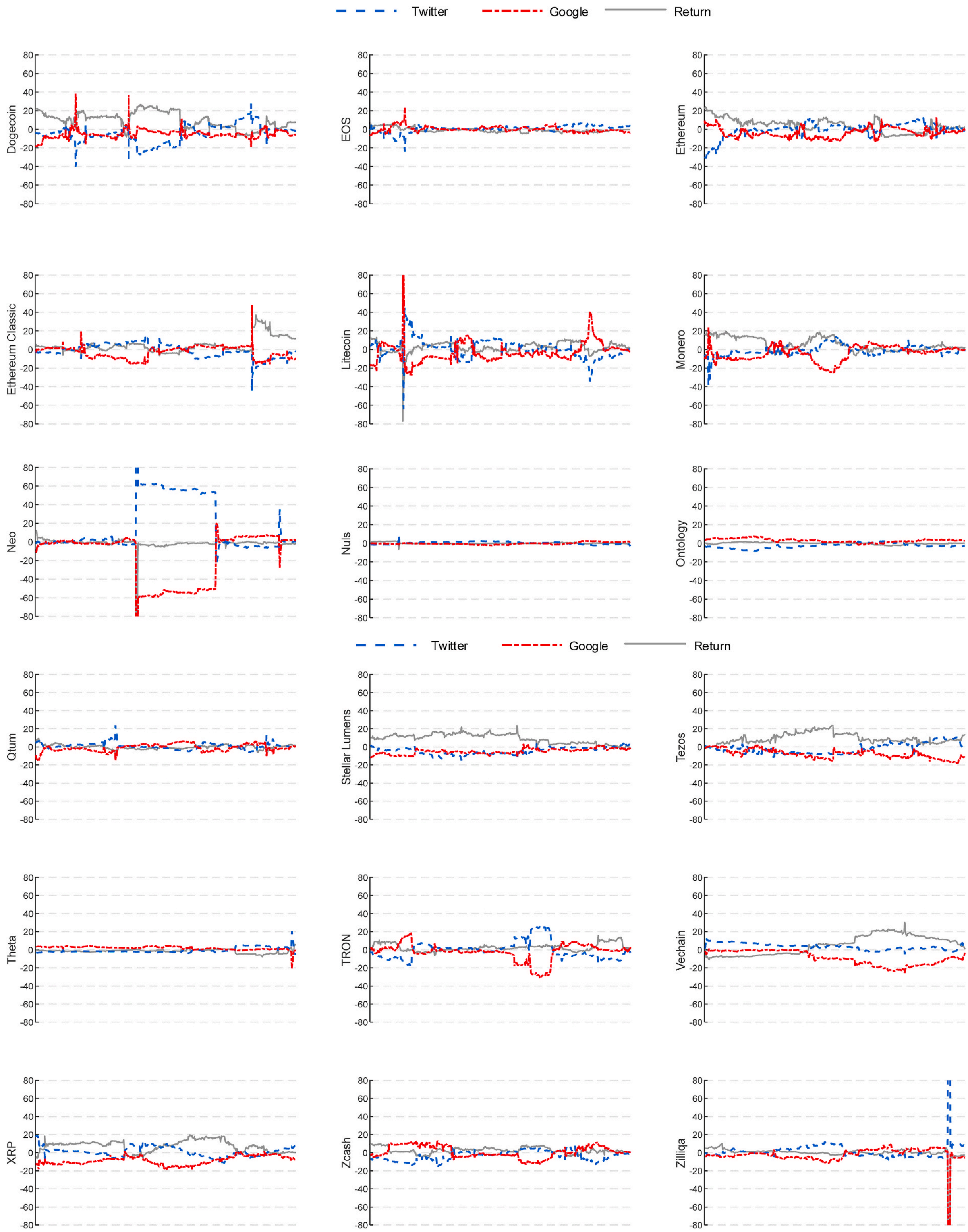


Fig. 1. (*continued*).

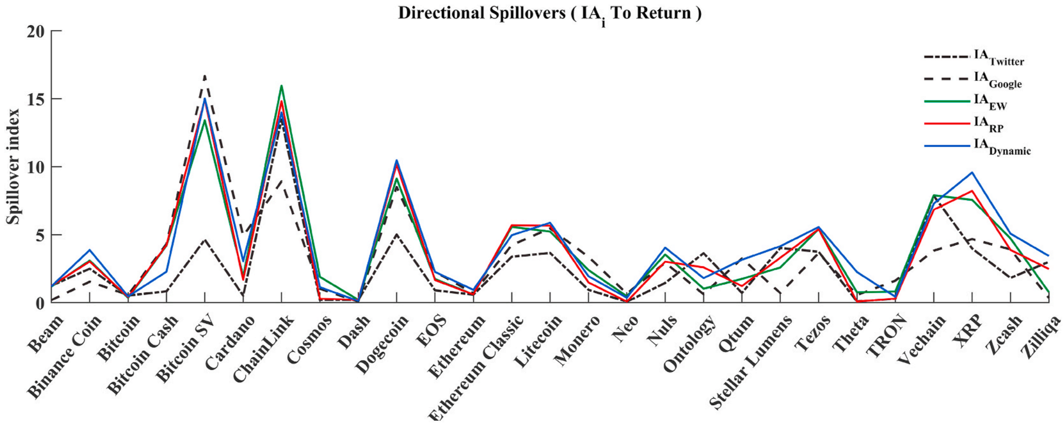


Fig. 2. Full-sample direction spillovers: $IA_{Twitter}$, IA_{Google}, IA_{EW}, IA_{RP} $IA_{Dynamic}$ and return for 27 cryptocurrencies.

5. Conclusions

Search-engine intensities signal important patterns of attention (Zhang & Tang, 2016). However, promotion of attention is considered by professional marketers to be most efficacious when a combination of search-engine and social-media marketing (Xiang & Gretzel, 2010; Yang et al., 2016). Consequently, finance research on investor attention, especially when employing Internet-based measures of attention, should consider closely how attention proxies are formed.

Considering that cryptocurrencies are particularly impacted by investor sentiment, we consider a focus on these currencies as ideal for investigating the relative impacts of differing forms of attention. We compare the bi-directional causality of cryptocurrency returns with investor attention, alternatively proxying investor attention with Twitter, as a form of social media, and Google Trends, as a form of search-engine intensity. We also investigate differing weightings between Twitter and Google. We examine 27 cryptocurrencies, using a non-parametric wavelet Granger causality test (NWGC) as an ideal tool that incorporates multiple time horizons. We also examine spillovers between cryptocurrencies and Google, Twitter, and weighted combinations of search-engine and social-media attentions.

Given the considerable interest in the impact of investor attention on investment returns, especially for cryptocurrencies, it is surprising that so little research examines comprehensively the bi-directional causalities between cryptocurrencies and investor attention. While studies alternatively proxy investor attention with either intensity of Twitter tweets or the intensity of Google searches, often limited to just Bitcoin, we compare the bi-directional causality of these different forms of social media with 27 cryptocurrencies, using a non-parametric wavelet Granger causality test as an ideal tool that can incorporate multiple time horizons. Results evidence a preponderance of bidirectional Granger causality between investor attention and the great majority of cryptocurrencies, with the impact of Twitter on cryptocurrencies being shorter term. We provide details for 27 cryptocurrencies regarding the nature of causality (direction, frequency) for both Twitter and Google, along with various combinations of these two measures of investor attention.

Additional testing with spillover analysis, confirms that as a proxy of investor attention, simple equal weightings of normalized Twitter and Google are economically more significant proxies for investor attention than either Twitter or Google used separately. Our results should be of great interest to academics and investors interested in the role of social media on financial markets.

Author statement

Yue Li: Data curation; Investigation; Methodology; Software; Writing – original draft; Validation; Visualization.

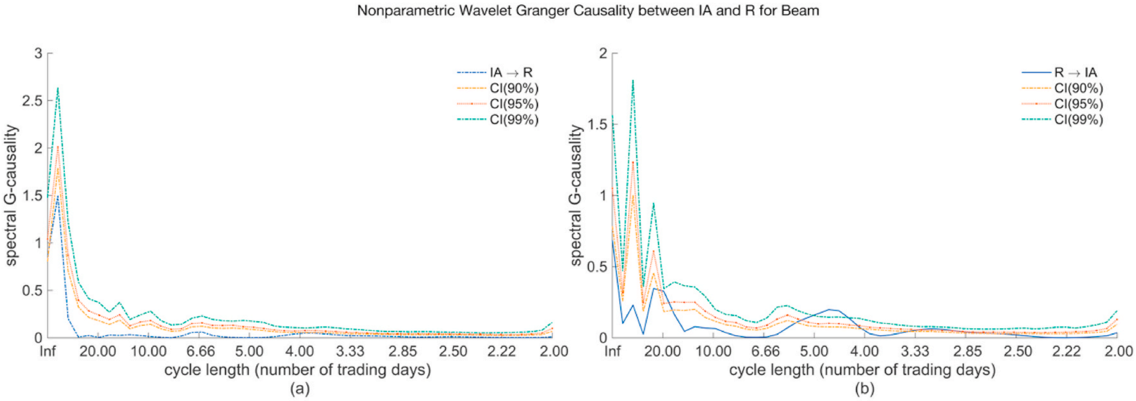
John W. Goodell: Formal analysis; Project administration; Resources; Supervision; Writing – original draft; Writing – review & editing.

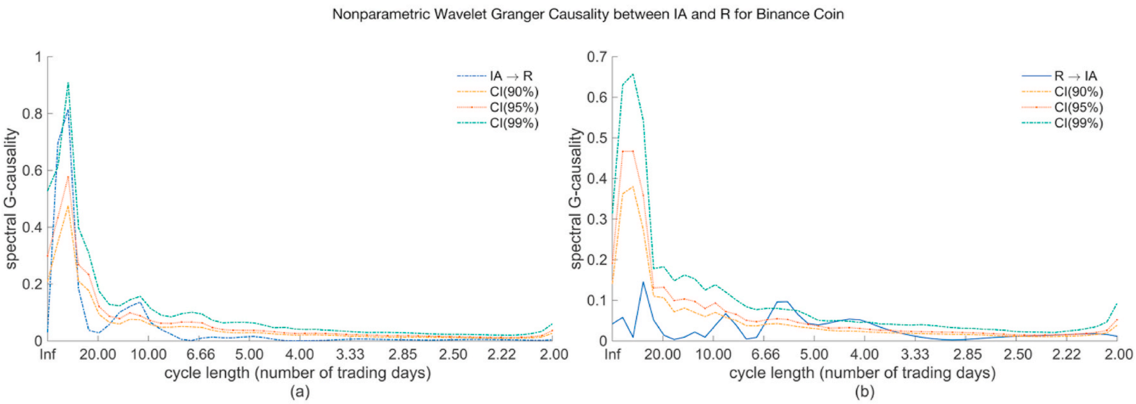
Dehua Shen: Conceptualization; Formal analysis; Funding acquisition; Methodology; Project administration; Software; Writing – original draft; Writing – review & editing.

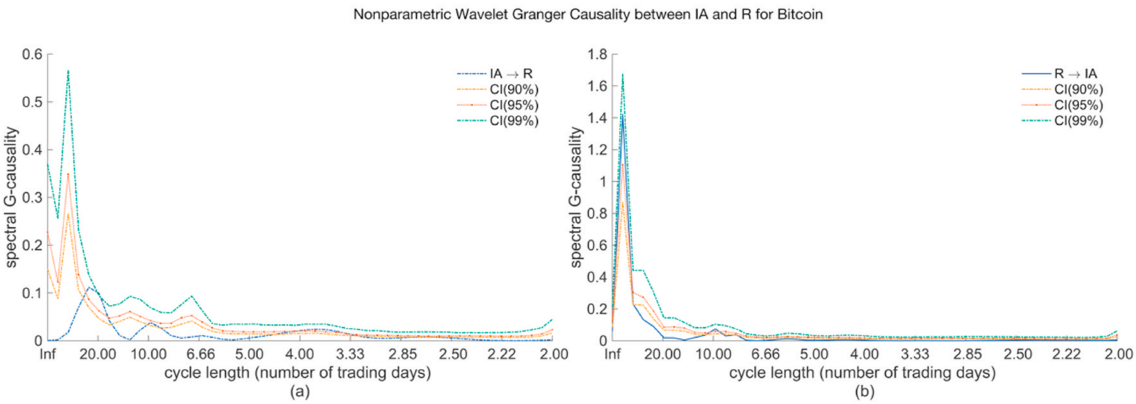
Acknowledgements

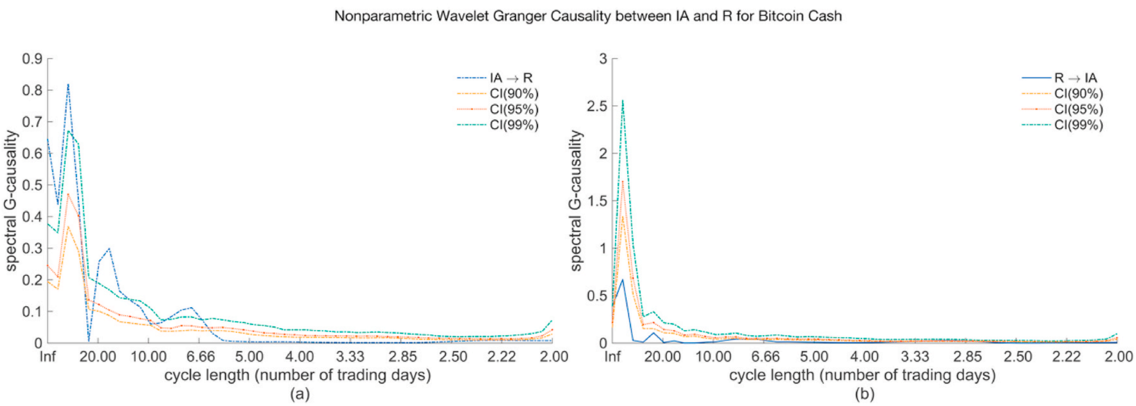
This work is supported by the National Natural Science Foundation of China (72071141). The authors are grateful to the Editor (Brian Lucey), and an anonymous referee. But the authors remain responsible for all errors.

Appendix A. Causality between cryptocurrency returns and normalized equal weighting of Google and Twitter

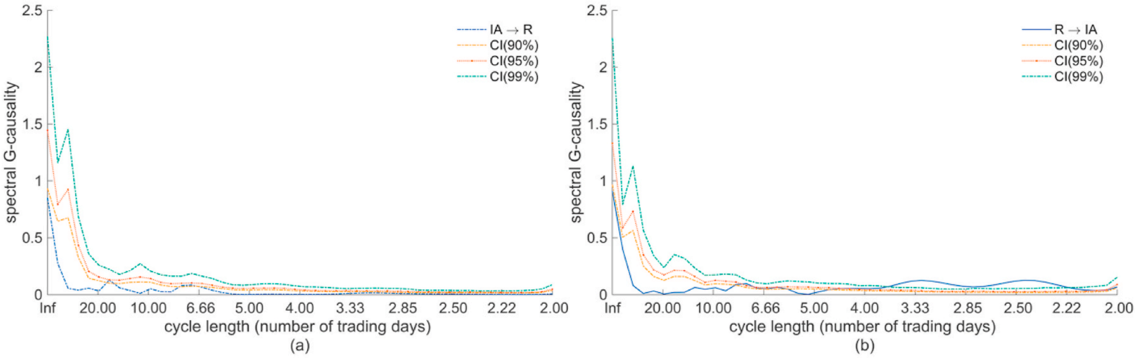

Nonparametric Wavelet Granger Causality between IA and R for Beam
spectral G-causality
cycle length (number of trading days)
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
(a)
(b)


Nonparametric Wavelet Granger Causality between IA and R for Binance Coin
spectral G-causality
cycle length (number of trading days)
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
(a)
(b)

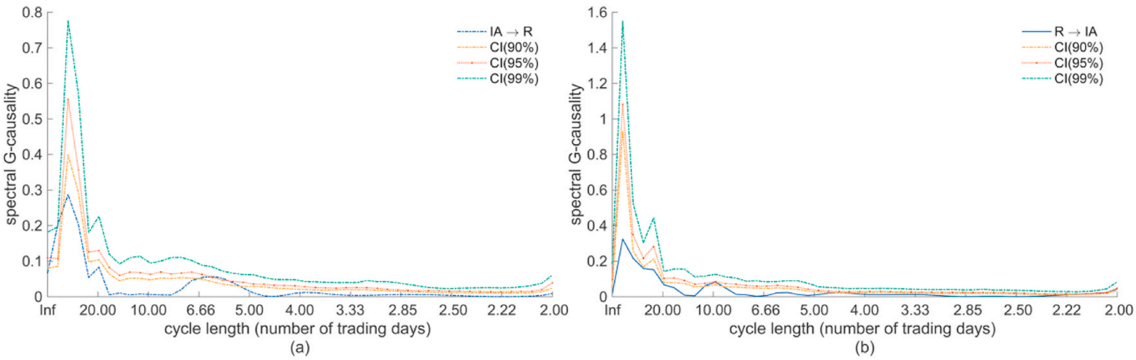

Nonparametric Wavelet Granger Causality between IA and R for Bitcoin
spectral G-causality
cycle length (number of trading days)
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
(a)
(b)


Nonparametric Wavelet Granger Causality between IA and R for Bitcoin Cash
spectral G-causality
cycle length (number of trading days)
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
(a)
(b)

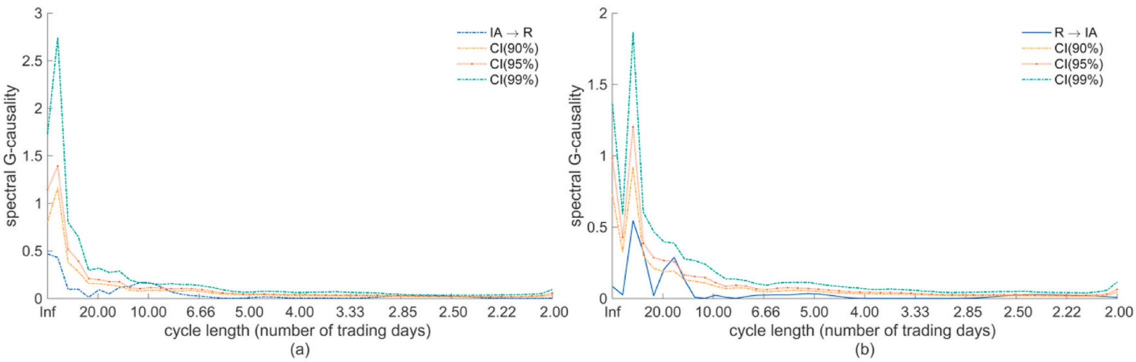
Nonparametric Wavelet Granger Causality between IA and R for Bitcoin SV



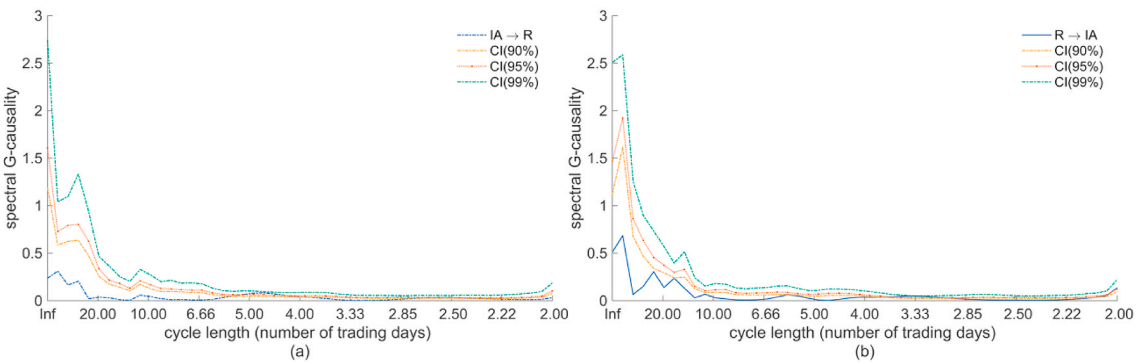
Nonparametric Wavelet Granger Causality between IA and R for Cardano



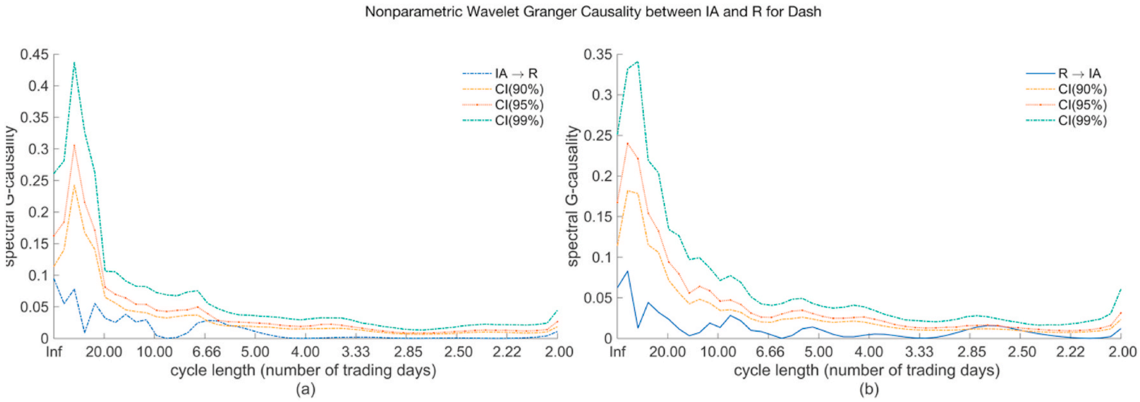
Nonparametric Wavelet Granger Causality between IA and R for ChainLink

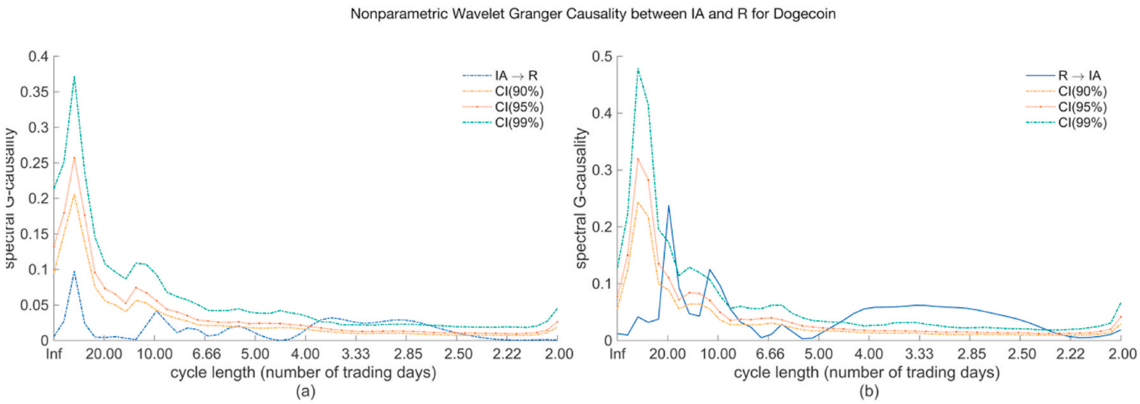


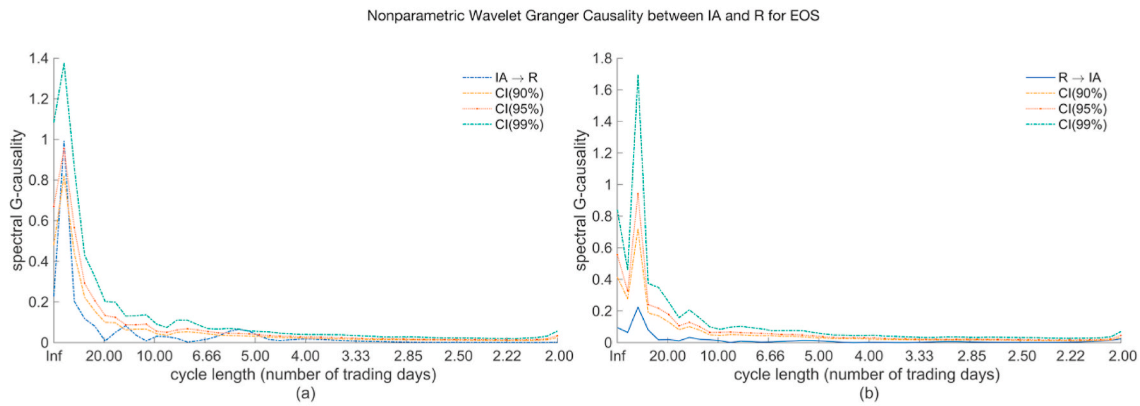
Nonparametric Wavelet Granger Causality between IA and R for Cosmos

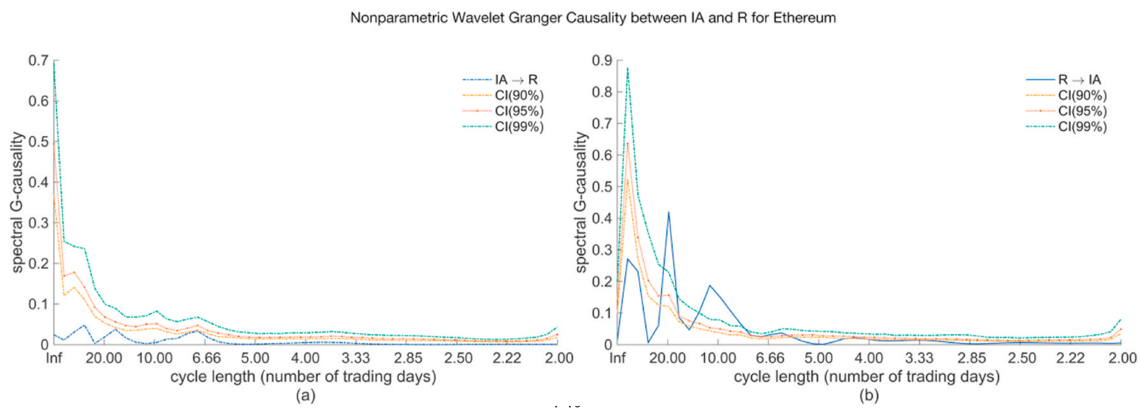


. (*continued*).


Nonparametric Wavelet Granger Causality between IA and R for Dash
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
spectral G-causality
cycle length (number of trading days)
(a)
(b)

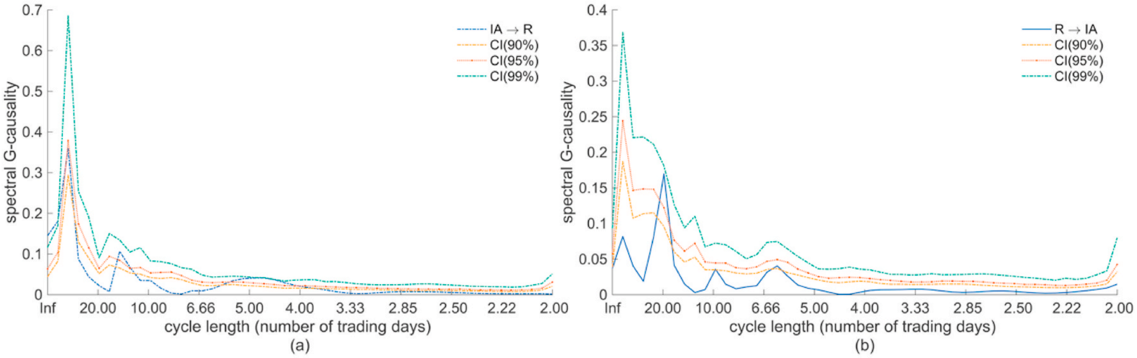

Nonparametric Wavelet Granger Causality between IA and R for Dogecoin
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
spectral G-causality
cycle length (number of trading days)
(a)
(b)


Nonparametric Wavelet Granger Causality between IA and R for EOS
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
spectral G-causality
cycle length (number of trading days)
(a)
(b)

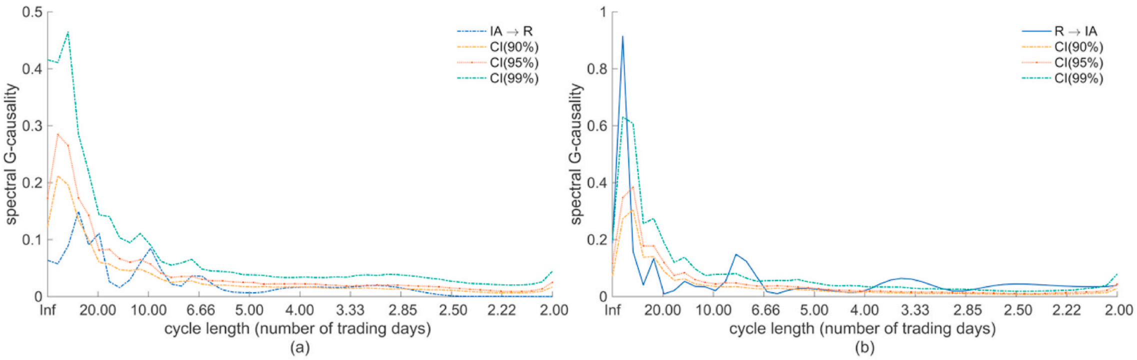

Nonparametric Wavelet Granger Causality between IA and R for Ethereum
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
spectral G-causality
cycle length (number of trading days)
(a)
(b)

. (*continued*).

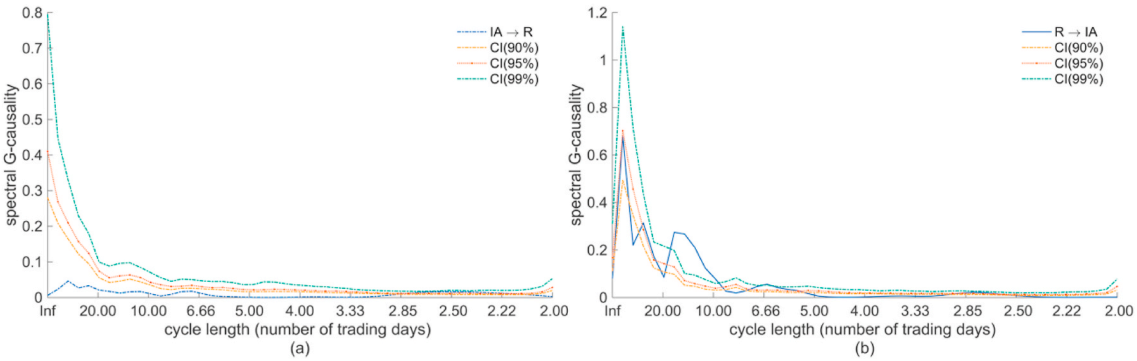
Nonparametric Wavelet Granger Causality between IA and R for Ethereum Classic



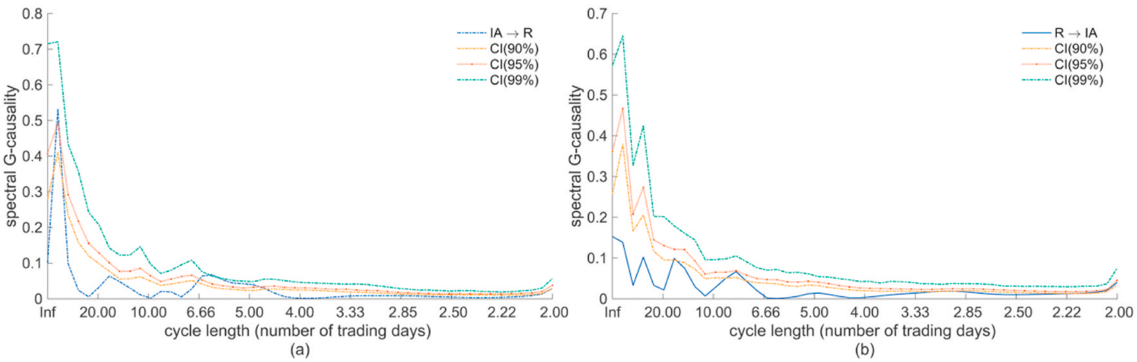
Nonparametric Wavelet Granger Causality between IA and R for Litecoin



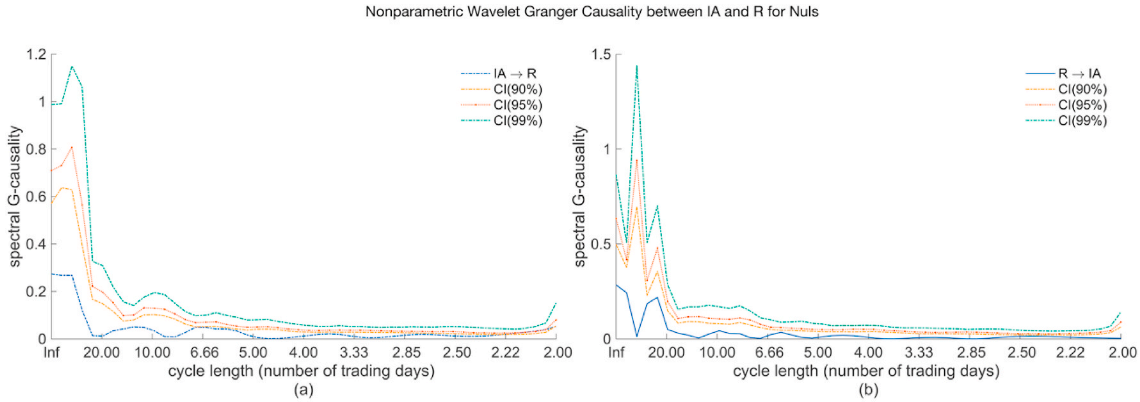
Nonparametric Wavelet Granger Causality between IA and R for Monero

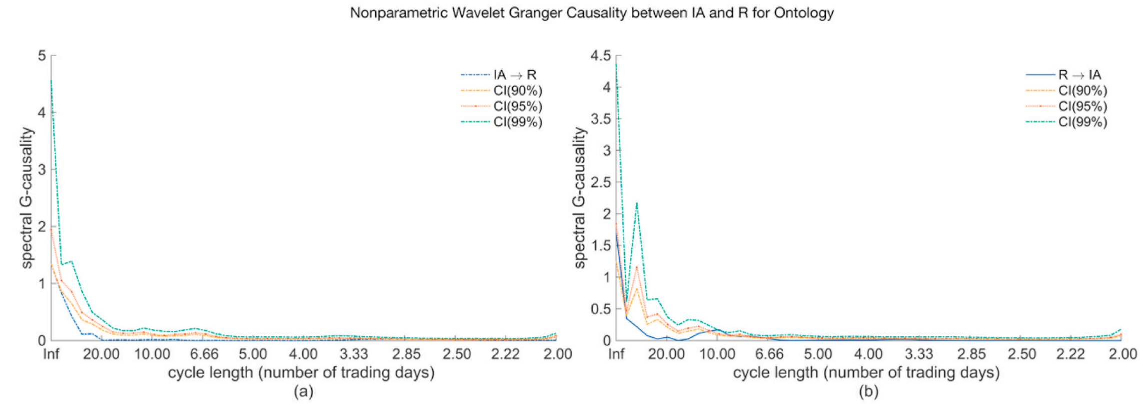


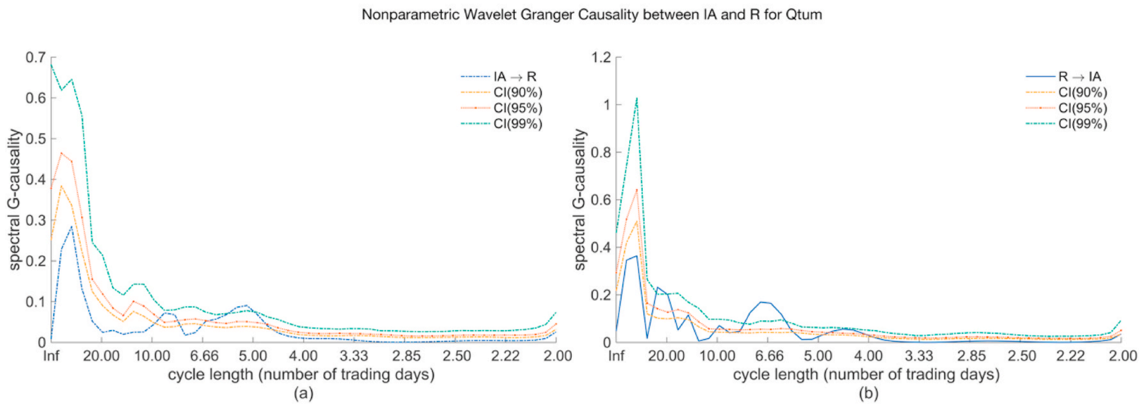
Nonparametric Wavelet Granger Causality between IA and R for Neo

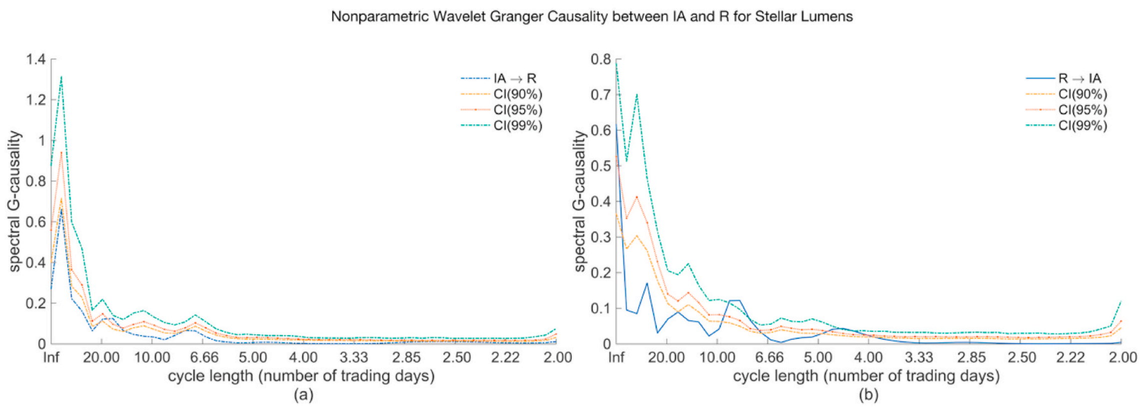


. (*continued*).


Nonparametric Wavelet Granger Causality between IA and R for Nuls
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
spectral G-causality
cycle length (number of trading days)
(a)
(b)

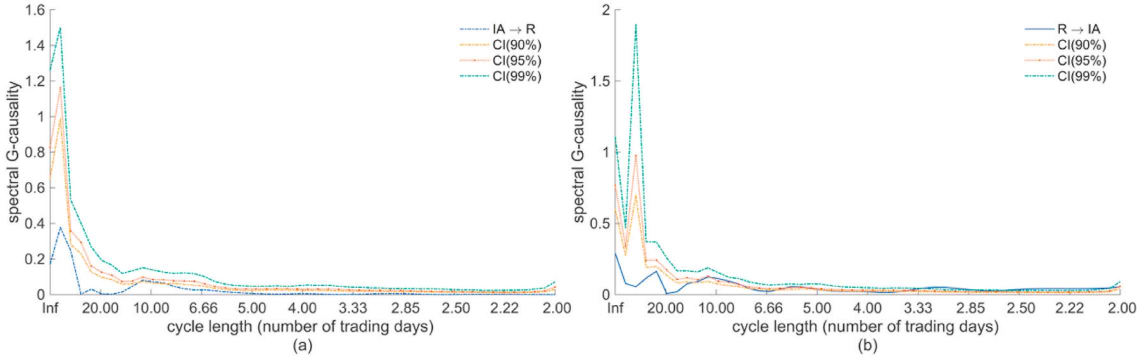

Nonparametric Wavelet Granger Causality between IA and R for Ontology
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
spectral G-causality
cycle length (number of trading days)
(a)
(b)


Nonparametric Wavelet Granger Causality between IA and R for Qtum
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
spectral G-causality
cycle length (number of trading days)
(a)
(b)

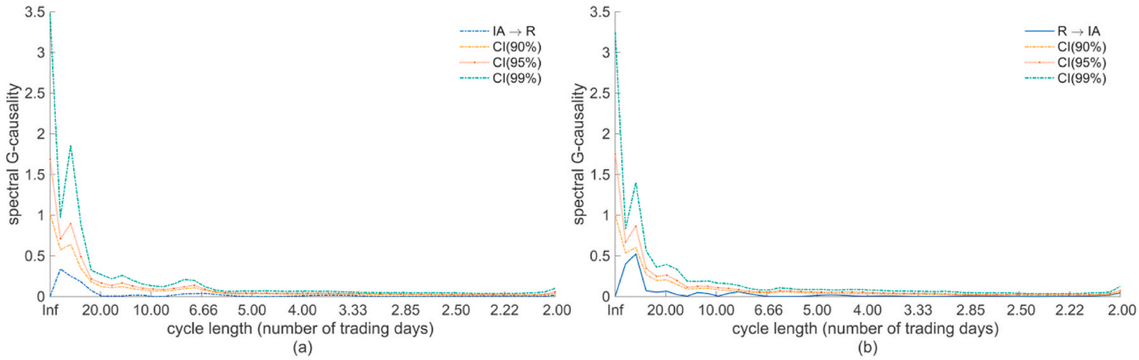

Nonparametric Wavelet Granger Causality between IA and R for Stellar Lumens
IA → R
R → IA
CI(90%)
CI(95%)
CI(99%)
spectral G-causality
cycle length (number of trading days)
(a)
(b)

. (*continued*).

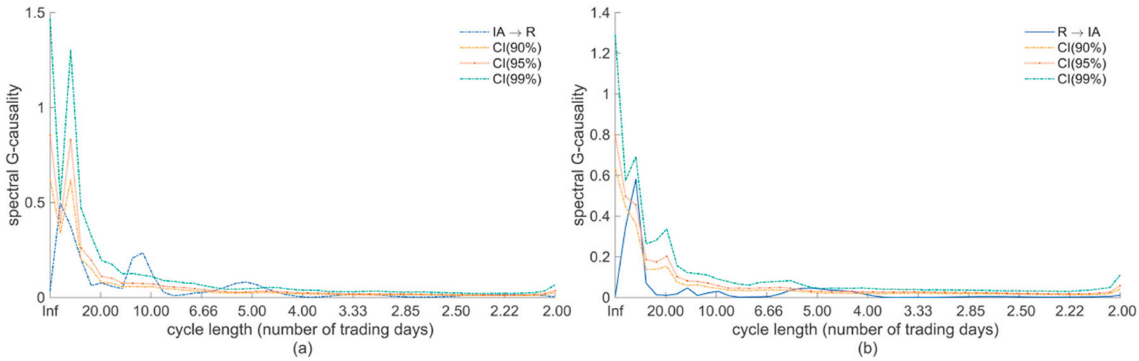
Nonparametric Wavelet Granger Causality between IA and R for Tezos



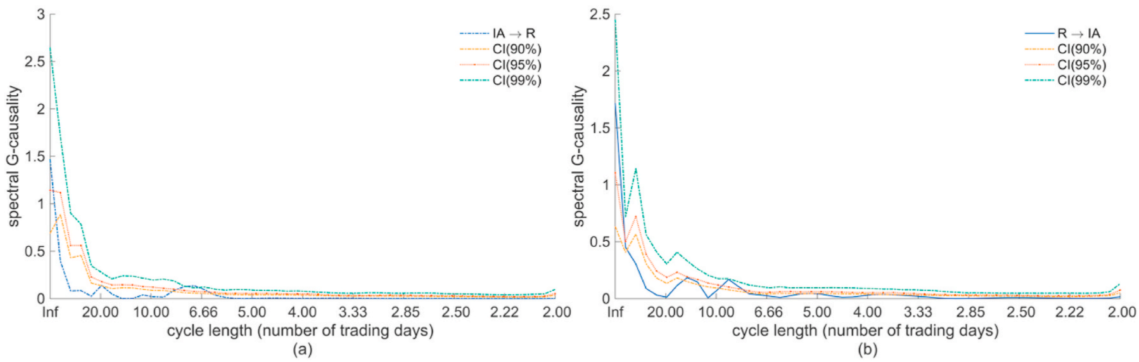
Nonparametric Wavelet Granger Causality between IA and R for Theta



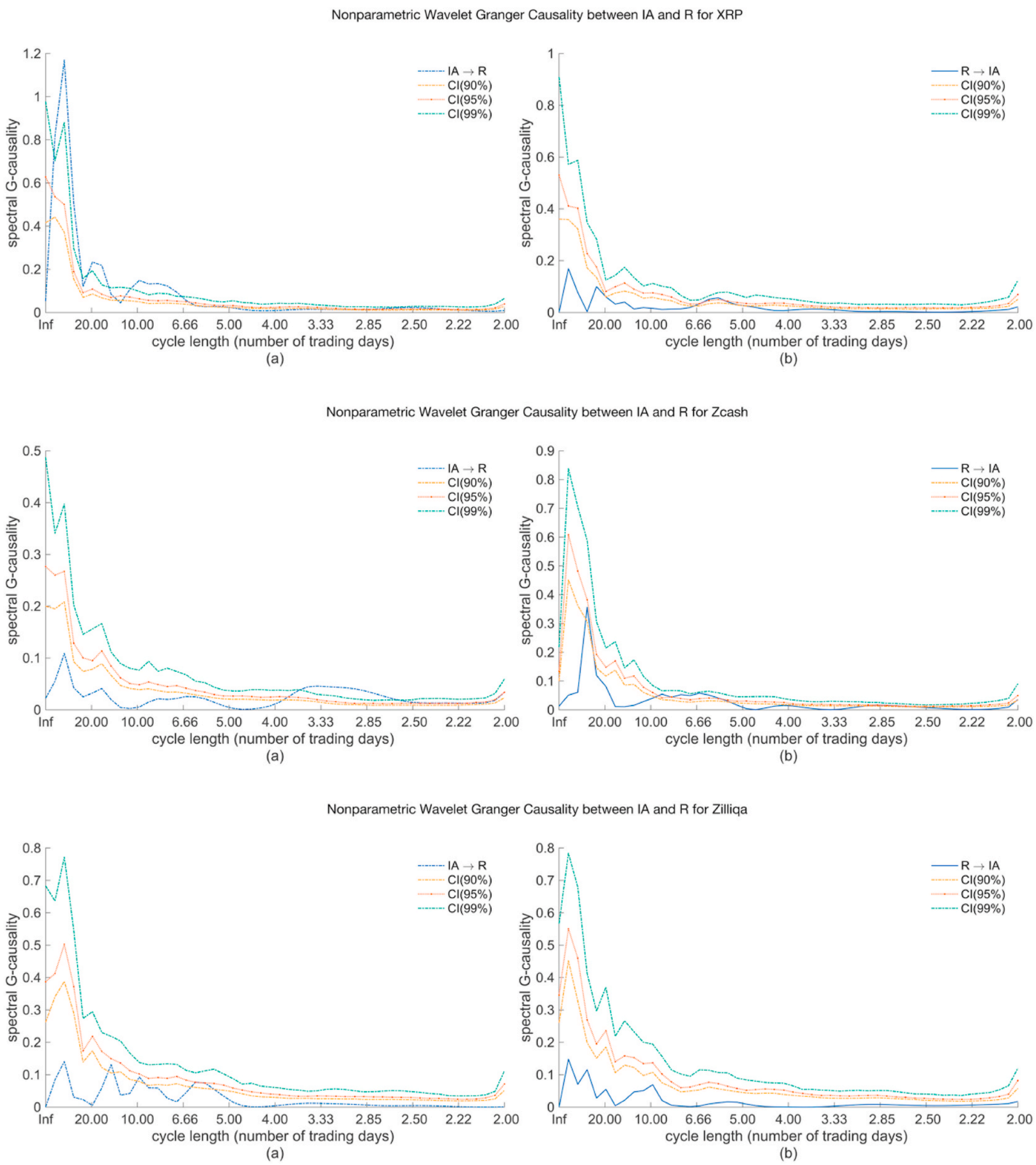
Nonparametric Wavelet Granger Causality between IA and R for TRON



Nonparametric Wavelet Granger Causality between IA and R for Vechain



. (*continued*).



. (*continued*).

Figure illustrates results of non-parametric wavelet Granger causality testing between investor attention proxied as an equal weighting of normalized intensities of Twitter tweets and Google searches (described in text) and returns on respective crypto-currencies. Blue dot-dash lines and Blue solid lines represent Granger causality from investor attention to returns and returns to investor attention respectively. Dot-dash green, red, and orange lines are respective 1%, 5%, and 10% statistical-significance lines. The null hypothesis of no causality in a given time scale is rejected if the causality coefficient lines jump over any significance level lines.

References

Antonakakis, N., Chatziantoniou, I., & George, F. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Economics, 44*, 433–447.

Benhmad, F. (2012). Modeling nonlinear granger causality between the oil price and U.S. Dollar: A wavelet based approach. *Economic Modelling, 29*(4), 1505–1514.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science, 2*(1), 1–8.

Chen, Y., Bressler, S. L., & Ding, M. (2006). Frequency decomposition of conditional Granger causality and application to multivariate neural field potential data. *Journal of Neuroscience Methods, 150*(2), 228–237.

Cheng, F., Chiao, C., Wang, C., Fang, Z., & Yao, S. (2021). Does retail investor attention improve stock liquidity? A dynamic perspective. *Economic Modelling, 94*, 170–183.

Conlon, T., & McGee, R. J. (2020). Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Finance Research Letters, 35*.

Corbet, S., Goodell, J. W., & Günay, S. (2020). Co-movements and spillovers of oil and renewable firms under extreme conditions: New evidence from negative WTI prices during COVID-19. *Energy Economics, 92*, Article 104978.

Corbet, S., Goodell, J. W., Gunay, S., & Kaskaloglu, K. (2021). *Are DeFi tokens a separate asset class from conventional cryptocurrencies?*. Working paper available SSRN.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*, 28–34.

Dastgir, S., Demir, E., Downing, G., Gozgor, G., & Lau, C. K. M. (2019). The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test. *Finance Research Letters, 28*, 160–164.

Detto, M., Molini, A., Katul, G., Stoy, P., Palmroth, S., & Baldocchi, D. (2012). Causality and persistence in ecological systems: A nonparametric spectral granger causality approach. *The American Naturalist, 179*(4), 524–535.

Dhamala, M., Rangarajan, G., & Ding, M. (2008a). Analyzing information flow in brain networks with nonparametric Granger causality. *NeuroImage, 41*(2), 354–362.

Dhamala, M., Rangarajan, G., & Ding, M. (2008b). Estimating granger causality from fourier and wavelet transforms of time series data. *Physical Review Letters, 100*(1).

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*(1), 57–66.

Diks, C., & Panchenko, V. (2006). A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics and Control, 30*(9–10), 1647–1669.

Ding, R., Zhou, H., & Li, Y. (2019). Social media, financial reporting opacity, and return comovement: Evidence from Seeking Alpha. *Journal of Financial Markets*, Article 100511.

Elshendy, M., Colladon Andrea, F., Battistoni, E., & Gloor, P. A. (2018). Using four different online media sources to forecast the crude oil price. *Journal of Information Science, 44*(3), 408–421.

Eross, A., Frank, M. G., Urquhart, A., & Wolfe, S. (2019). The intraday dynamics of bitcoin. *Research in International Business and Finance, 49*, 71–81.

Gao, X., & Lin, T.-C. (2015). Do individual investors treat trading as a fun and exciting gambling activity? Evidence from repeated natural experiments. *Review of Financial Studies, 28*(7), 2128–2166.

Geweke, J. (1982). Measurement of linear dependence and feedback between multiple time series. *Journal of the American Statistical Association, 77*(378), 304–313.

Goodell, J. W., & Goutte, S. (2021a). Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. *Finance Research Letters, 38*, Article 101625.

Goodell, J. W., & Goutte, S. (2021b). Diversifying with cryptocurrencies during COVID-19. *International Review of Financial Analysis, 76*, 101781.

Goodell, J. W., & Luu Duc Huynh, T. (2020). Did congress trade ahead? Considering the reaction of US industries to COVID-19. *Finance Research Letters, 36*.

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica, 37*(3), 424–438.

Guégan, D., & Renault, T. (2021). Does investor sentiment on social media provide robust information for Bitcoin returns predictability? *Finance Research Letters, 38*, Article 101494.

Guo, T., Finke, M., & Mulholland, B. (2015). Investor attention and advisor social media interaction. *Applied Economics Letters, 22*(4), 261–265.

Gupta-Mukherjee, S., & Pareek, A. (2016). Limited attention and portfolio choice: The impact of attention allocation on mutual fund performance. *Financial Management, 49*(4), 1083–1125.

Huang, S., Huang, Y., & Lin, T.-C. (2019). Attention allocation and return co-movement: Evidence from repeated natural experiments. *Journal of Financial Economics, 132*(2), 369–383.

Hu, Y., Xiao, L., Goodell, J. W., & Shen, D. (2021). Investor attention shocks and stock co-movement: Substitution or reinforcement? *International Review of Financial Analysis, 73*, Article 101617.

Ibikunle, G., Frank, M. G., & Rzayev, K. (2020). More heat than light: Investor attention and bitcoin price discovery. *International Review of Financial Analysis, 69*, Article 101459.

Ibikunle, G., Frank, M. G., & Rzayev, K. (2020). More heat than light: Investor attention and bitcoin price discovery. *International Review of Financial Analysis, 69*, Article 101459.

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance, 50*, 322–335.

Katsiampa, P., Corbet, S., & Lucey, B. (2019a). High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money, 62*, 35–52.

Katsiampa, P., Corbet, S., & Lucey, B. (2019b). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters, 29*, 68–74.

Kristoufek, L. (2013). BitCoin meets Google trends and wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports, 3*, 3415.

Kyriazis, N., Papadamou, S., & Corbet, S. (2020). A systematic review of the bubble dynamics of cryptocurrency prices. *Research in International Business and Finance, 54*, Article 101254.

Li, S., Zhang, H., & Yuan, Di (2019). Investor attention and crude oil prices: Evidence from nonlinear Granger causality tests. *Energy Economics, 84*, Article 104494.

Mensi, W., Ur Rehman, M., Maitra, D., Al-Yahyaee, K. H., & Sensoy, A. (2020). Does bitcoin co-move and share risk with sukuk and world and regional islamic stock markets? Evidence using a time-frequency approach. *Research in International Business and Finance*, Article 101230.

Naeem, M. A., Mbarki, I., & Shahzad, S. J. H. (2021). Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears. *International Review of Economics & Finance, 73*, 496–514.

Omane-Adjepong, M., & Alagidede, I. P. (2019). Multiresolution analysis and spillovers of major cryptocurrency markets. *Research in International Business and Finance, 49*, 191–206.

Philippas, D., Rjiba, H., Guesmi, K., & Goutte, S. (2019). Media attention and Bitcoin prices. *Finance Research Letters, 30*, 37–43.

Piñeiro-Chousa, J., López-Cabarcos, M.Á., Pérez-Pico, A. M., & Ribeiro-Navarrete, B. (2018). Does social network sentiment influence the relationship between the S&P 500 and gold returns? *International Review of Financial Analysis, 57*, 57–64.

Rakowski, D., Shirley, S. E., & Stark, J. R. (2019). Twitter activity, investor attention, and the diffusion of information. *Financial Management, 50*(1), 3–46.

Reboredo, J. C., & Ugolini, A. (2018). The impact of Twitter sentiment on renewable energy stocks. *Energy Economics, 76*, 153–169.

Schreiber, T., & Schmitz, A. (2000). Surrogate time series. *Physica D, 142*(3–4), 346–382.

Shen, D., Urquhart, A., & Wang, P. (2019). Does twitter predict Bitcoin? *Economics Letters, 174*, 118–122.

Torun, E., Chang, T.-P., & Chou, R. Y. (2020). Causal relationship between spot and futures prices with multiple time horizons: A nonparametric wavelet granger causality test. *Research in International Business and Finance, 52*.

Urquhart, A. (2018). What causes the attention of Bitcoin? *Economics Letters, 166*, 40–44.

Wilson, G. T. (1972). The factorization of matricial spectral densities. *SIAM Journal on Applied Mathematics, 23*(4), 420–426.

Wilson, G. T. (1978). A convergence theorem for spectral factorization. *Journal of Multivariate Analysis, 8*(2), 222–232.

Xiang, Z., & Gretzel, U. (2010). Role of social media in online travel information search. *Tourism Management, 31*(2), 179–188.

Yang, S., Lin, S., Carlson, J. R., & Ross, W. T. (2016). Brand engagement on social media: Will firms' social media efforts influence search engine advertising effectiveness? *Journal of Marketing Management, 32*(5–6), 526–557.

Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting stock market indicators through twitter "I hope it is not as bad as I fear". *Procedia-Social and Behavioral Sciences, 26*, 55–62.

Zhang, Z., & Tang, W. (2016). Analysis of spatial patterns of public attention on housing prices in Chinese cities: A web search engine approach. *Applied Geography, 70*, 68–81.

Zhang, W., & Wang, P. (2020). Investor attention and the pricing of cryptocurrency market. *Evolutionary and Institutional Economics Review, 17*, 445–468.

Zhang, Z., Zhang, Y., Shen, D., & Zhang, W. (2018). The cross-correlations between online sentiment proxies: Evidence from Google Trends and Twitter. *Physica A: Statistical Mechanics and Its Applications, 508*, 67–75.

Zhaunerchyk, K., Haghighi, A., & Oliver, B. (2020). Distraction effects on stock return co-movements: Confirmation from the Shenzhen and Shanghai stock markets. *Pacific-Basin Finance Journal*, Article 101301.