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Do online attention and sentiment affect cryptocurrencies' correlations?

Nektarios Aslanidis [a], Aurelio F. Bariviera [b,*], Christos S. Savva [c]

[a] Universitat Rovira i Virgili, Department d'Economia, ECO-SOS, Av. Universitat 1, 43204 Reus, Spain
[b] Universitat Rovira i Virgili, Department of Business, ECO-SOS, Av. Universitat 1, 43204 Reus, Spain
[c] Department of Finance, Accounting and Management Science, Cyprus University of Technology, P.O Box 50329, 3603 Limassol, Cyprus

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ABSTRACT

This paper adopts a versatile conditional correlation approach to explore daily seasonality in the major cryptocurrencies. Given the lack of clear fundamental value in this market and the active online profile of investors, the study also relates cryptocurrency cross-correlations to online market attention and sentiment. Our results highlight that while investor attention has a positive effect, sentiment has a much stronger negative impact on the correlations. These findings can offer interesting insights for investors and regulators, as the influence of market attention and sentiment on the correlations has important implications for portfolio diversification and market stability.

1. Introduction

The rapid growth and volatility of the cryptocurrency market in recent years has sparked significant academic interest and research (Corbet et al., 2019; Merediz-Solà and Bariviera, 2019). Scholars have sought to better understand the factors driving the value and returns of cryptocurrencies and other digital tokens. Cong et al. (2021) develop a theoretical model of a token market and find that token value is a consequence of users' endogenous activities, and that such activities play a key role in the cross-section of returns. Such users' activities can likely be driven by news and sentiment about the market. In line with Liu and Tsyvinski (2021) and Smales (2022), Sockin and Xiong (2023) put forward a model for cryptocurrencies, which points out the importance of news and investor sentiment in determining cryptocurrency market movements. Liu et al. (2022) take an asset pricing approach to construct three cryptocurrency factors: market, size, and momentum. They provide evidence that the size and momentum factors have predictive ability in the cross-section of cryptocurrency returns.

One key consequence of the online-centric cryptocurrency market is that investors tend to rely heavily on web-based information sources (web searches, online forums, etc.) to gather relevant data and insights. Consequently, two important topics have emerged in the literature: (a) Investors in cryptocurrencies often rely heavily on information from the internet to assess their value, as it can be challenging to measure fundamental values. Studies have found that factors such as Google Trends attention (Urquhart, 2018; Aslanidis et al., 2022), Google Trends sentiment (Liu and Tsyvinski, 2021; Smales, 2022), and forum engagement (Dias et al., 2022) are significant determinants of the cryptocurrency market; (b) Similar to traditional financial markets like stocks and bonds,

* Corresponding author.
E-mail address: aurelio.fernandez@urv.cat (A.F. Bariviera).

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researchers have also examined the presence of abnormal returns due to daily seasonality in cryptocurrency markets (Mbanga, 2019; Ma and Tanizaki, 2019; Caporale and Plastun, 2019; Aharon and Qadan, 2019).

This paper combines previous literature to explore day-of-the-week seasonality in cryptocurrencies relative to online market attention and sentiment. To this end, we model daily seasonality in a unified econometric framework encompassing returns, volatilities, and, more importantly, cross-correlations. Additionally, we adopt an online activity approach to capture online investor attention and sentiment by means of Google Trends.

We contribute to the literature as follows: (i) We revisit the day-of-the-week effect on returns and volatility, while offering new evidence of seasonality for the cross-correlations between cryptocurrencies; (ii) Unlike previous studies, we examine seasonality adopting a more versatile multivariate volatility framework, namely the *Periodic Generalized Dynamic Conditional Correlation* model, proposed by Osborn et al. (2008); (iii) We report a substantial day-of-the-week effect in cryptocurrencies' correlations, except perhaps for the period around the outbreak of the COVID-19 pandemic; (iv) To the best of our knowledge, we are the first to document the link between cryptocurrencies' correlation and investor attention and sentiment. In particular, investor attention has a positive, albeit small, effect on the correlations, whereas investor sentiment has a negative and significantly stronger effect.

Our analysis offers useful insights for academics, practitioners, and policymakers. The cryptocurrency market provides an opportunity to study the behavior of a *purely* speculative asset. Fama (2015), major fund managers (Buffett, 2018), academic research (Cheah and Fry, 2015) and a recent blog post by experts at the European Central Bank (Bindseil and Schaaf, 2024) argue that Bitcoin has no intrinsic value and its fundamental value is close to zero. This characteristic of cryptocurrencies provides an ideal environment to study the effect of online market attention and sentiment. From a practitioner's point of view, the influence of attention and sentiment can provide hints to design products and innovative investment strategies. Given the growing importance of the cryptocurrency market, policymakers should take a closer look at sudden changes in market attention and sentiment, as they can put the overall financial stability at risk.

The rest of the paper is structured as follows. Section 2 gives an overview of the relevant literature on cryptocurrencies' studies. Section 3 introduces the methodology used in this paper. Section 4 details the data under analysis and comments on the main findings of our study. Finally, Section 5 draws the main conclusions.

2. Literature review

This section classifies the literature into four parts, namely, (i) The Efficient Market Hypothesis; (ii) Asset correlation and portfolio optimization; (iii) Day-of-the-week effect; and (iv) Market attention and sentiment. These four strands of the literature underpin the theoretical framework for our cryptocurrency analysis.

2.1. *The efficient market hypothesis*

The traditional definition of informational efficiency is from Fama (1970) and corresponds to a market where prices fully reflect all available information. In its weak form, it means that returns should follow a random walk process. The Efficient Market Hypothesis (EMH) is a sufficient condition for the existence of equilibrium in a competitive market, in which arbitrage opportunities cannot exist. Ross (2005) indicates that this definition evokes the idea that prices are the result of decisions by individual agents and, therefore, depend on the underlying information.

The early literature on cryptocurrencies was mainly devoted to testing the Efficient Market Hypothesis (EMH) in this market. Urquhart (2016) used a set of tests aimed at identifying autocorrelations, unit roots, nonlinearities, and long-range dependence in Bitcoin returns. The results showed evidence of initial information inefficiency in the Bitcoin market.

However, subsequent studies have found that informational efficiency in the Bitcoin market has increased over time. Nadarajah and Chu (2017) reexamined (Urquhart, 2016) using power transformations of daily returns and did not reject the null hypothesis of informational efficiency. Bouri et al. (2017) scrutinized the hedge and safe-haven properties of Bitcoin *vis-à-vis* international stock and bond indices and several currencies, finding that Bitcoin proves more useful as a diversifier rather than as a hedge instrument.

Furthermore, Bariviera (2017) found that while the Bitcoin market has become more informationally efficient over time, it still exhibits persistence in volatility. This means that periods of high (low) volatility tend to be followed by periods of high (low) volatility, indicating that the market has not fully eliminated inefficiencies related to volatility clustering. Taking this into account, Donier and Bouchaud (2015) studied different measures of liquidity as early warning signs of Bitcoin market crashes.

2.2. *Assets correlation and portfolio optimization*

One key aspect in portfolio theory, and broadly in financial economics, is the correct assessment of the correlation between returns among different assets. Such a metric has important implications regarding portfolio construction, risk analysis, and hedging. Corbet et al. (2018) employ the generalized variance decomposition methodology by Diebold and Yilmaz (2012). They find that the three major cryptocurrencies (Bitcoin, Ripple, Litecoin) are rather isolated from other assets such as gold, stocks or bonds, offering diversification opportunities to investors. In a similar vein, the study by Aslanidis et al. (2019) finds a positive but time-varying conditional correlation among cryptocurrencies (Bitcoin, Ripple, DASH, Monero) and confirms that the exposure of cryptocurrencies to traditional assets is generally low. Borri (2019)' risk management analysis revealed that cryptocurrencies face significant tail-risk within cryptocurrency markets, but do not exhibit the same tail-risk exposure when compared to traditional assets like U.S. stocks and gold. Li and Miu (2023) adopt a regime-switching model to test for state-dependent correlation between stock-cryptocurrency returns. They document that the correlation is conditional on the volatility regimes of the two assets: (i) The correlation is positive and significant when both markets are under high-volatility states, and, (ii) The correlation is insignificant or even negative in lower volatility states.

2.3. Day-of-the-week effect

Daily and monthly seasonality are recurring topics in financial economics. The presence of abnormal returns on a particular day is described under the generic name of "day-of-the-week effect". The existence of this anomaly is based on the assumption that financial market returns should be equal across the week. The origins of this effect can be traced back to Fields (1931, 1934), who investigated the propensity of investors to sell on the last day of the trading week in order to avoid uncertainty over the weekend. Research on daily seasonality began to gain momentum in the 1970s and 1980s. For instance, Cross (1973) documented abnormal returns on Mondays and Fridays in the US market. Subsequently, French (1980) reexamined the US market and divided the effect into the Monday effect (which refers to the fact that this day has a negative return) and the Friday effect (abnormal and significantly high returns on this day). Condoyanni et al. (1987) extended the US results to several other countries (Australia, Canada, France, Japan, Singapore, and the United Kingdom) for the period 1969–1984. The day-of-the-week effect has also been found for other financial assets such as bond markets (Alexander and Ferri, 2000).

There are several alternative explanations for such abnormal behavior, but none of them is completely satisfactory. Lakonishok and Levi (1982) provide a partial explanation for this effect, based on the delays in transaction settlements and checks' clearing. They also interpret the Monday effect as a correction of Friday's excess performance. Lakonishok and Maberly (1990) explain part of the effect through patterns in the behavior of individual and institutional investors. Admati and Pfleiderer (1988) indicate that the day-of-the-week effect could be caused by the interaction between informed traders and liquidity traders. There are other attempts at explanation, but it is still an open issue in financial economics.

In the case of cryptocurrencies, daily seasonality is a more complex puzzle, because there are no market closings, nor holidays, and non-homogeneous institutional practices. Studies conducted so far have been based on univariate models. Caporale and Plastun (2019) examine the day-of-the-week effect in Bitcoin, Litecoin, Ripple, and Dash, finding evidence of this anomaly only in the case of Bitcoin. Ma and Tanizaki (2019) find that the weekly seasonality varies with the sample period and that Mondays and Thursdays are generally associated with higher volatilities. Kinateder and Papavassiliou (2019) show evidence of a Wednesday effect in returns. Aharon and Qadan (2019) reports day-of-the-week effect for Bitcoin at both return and variance.

2.4. Market attention and sentiment

Several papers have discussed the way financial markets react to increased uncertainty by taking into consideration investor sentiment (for recent contributions see Jiao et al. (2020), Chen et al. (2021), Agoraki et al. (2022), among others). Investor sentiment reflects agents' beliefs and emotions about asset price deviations from their fundamental values. In a seminal paper, Baker and Wurgler (2006) find that when investor sentiment is low, expected returns are high particularly for small and highly volatile US stocks. Siganos et al. (2014) take an international approach to provide evidence that sentiment has a positive relation to expected returns in 20 international stock markets.

Early studies on investor sentiment employ market data such as trading volume, closed-end fund discount, dividend premium, or average first-day returns on IPOs as a proxy for market sentiment (Barberis et al., 1998; Baker and Wurgler, 2006). Instead, another strand of the literature focuses on measures of sentiment based on textual analysis. Shiller (2015) and Tetlock (2007) argue that the news media can play an important role in financial market movements, while García (2013) and Manela and Moreira (2017) construct text-based proxies for the US market sentiment and for uncertainty, respectively. Overall, the important role played by sentiment echoes the narrative economics story put forward by Shiller (2017).

Due to the lack of clear fundamental value in cryptocurrencies and the active online presence of cryptocurrency investors, several studies have adopted a textual analysis approach to assess investor sentiment. For instance, Urquhart (2018) is one of the earliest papers to relate cryptocurrency's market attention with Google Trends, finding that realized volatility, volume, and returns influence the future search for the term 'Bitcoin'. Lucey et al. (2022) constructed cryptocurrency uncertainty indices based on a variety of news pieces from the LexisNexis Business Database. Building on Urquhart (2018), Liu and Tsyvinski (2021) and Aslanidis et al. (2022) revisit the linkage between cryptocurrencies and online searches. Using Google Trends, Liu and Tsyvinski (2021) construct a cryptocurrency sentiment index and find that sentiment strongly forecasts future cryptocurrency returns. Instead, Aslanidis et al. (2022) construct a cryptocurrency attention index based on Google Trends and show that cryptocurrencies are mainly linked to such a specific index, rather than to an economy-wide Google Trends attention index. In a similar vein, Shi et al. (2024) investigate information transfer between GameFi token returns and investor attention, finding that investor attention is particularly relevant for tokens with lower liquidity.

Moreover, Guégan and Renault (2021) investigate the social media component of sentiment to explore the relationship between sentiment and Bitcoin returns, while Sapkota (2022) examines the effect of sentiment on bitcoin volatility. Li et al. (2021) compare the intensity of Google searches and Twitter activity, as well as a combined measure of both attention proxies. They find a bidirectional relationship between these metrics, with the impact of Twitter activity generally being shorter-lived. Additionally, combining the proxies strengthened the observed bidirectional causality. Akyildirim et al. (2021) take a multivariate approach to consider the dynamic network connectedness between cryptocurrency returns and sentiment and find that information transmission is from cryptocurrency returns towards sentiment and not vice versa. Finally, Narayanasamy et al. (2023) provide evidence of a relationship between investor sentiment and bitcoin futures and spot prices, whereas investor attention is solely linked to spot prices.

3. Periodic dynamic conditional correlations

The current paper adopts insights from the *Periodic Generalized Dynamic Conditional Correlation* (PG-DCC) methodology by Osborn et al. (2008) to model the correlations between major cryptocurrencies. This methodology extends the *Generalized Dynamic Conditional Correlation* model (Cappiello et al., 2006) to allow for seasonality in the conditional returns, in the conditional volatility and in the conditional correlations between the assets. If seasonality is ignored, the estimates are likely to be biased.

Consider the following N-dimensional vector process of stock returns, $y_t = [y_{1,t}, \dots, y_{N,t}]'$:

$$y_t = \sum_{s=1}^{7} \left[\mu_s + \sum_{l=1}^{p} \phi_{ls} y_{t-l} \right] D_{s,t} + \varepsilon_t, \qquad t = 1, \dots, T \tag{1}$$

where the scalar $D_{s,t}$ is a dummy variable indicating the day of the week s ($s = 1, 2, 3, 4, 5, 6, 7$), while p ($p = 1, \dots, 7$) is the order of the autoregression. The conditional covariances of the shocks in Eq. (1) are time-varying, such that:

$$\varepsilon_t | \Im_{t-1} \sim H_t \tag{2}$$

where $\Im_{t-1}$ is the information set at time t. We follow the literature (see Engle (2002), among others) and decompose the conditional covariance matrix as:

$$H_t = D_t R_t D_t \tag{3}$$

where $D_t \equiv diag\left(\sqrt{h_{1,t}}, \dots, \sqrt{h_{N,t}}\right)$ is a diagonal matrix with the square root of the conditional variances on the diagonal. The matrix R_t,with the (i,j)-th element denoted as $\rho_{ij,t}$, is the possibly time-varying correlation matrix with $\rho_{ii,t} = 1, i = 1, \dots, N$ and $t = 1, \dots, T$. Each of the univariate error processes follows a periodic EGARCH$(1,1)$ specification:

$$\varepsilon_{i,t} = \sqrt{h_{i,t}} v_{it} \tag{4}$$

$$h_{i,t} = \sum_{s=1}^{7} \left[\exp\{\omega_{is} + \gamma_{is} v_{i,t-1} + \theta_{is}(|v_{i,t-1}| - E|v_{i,t-1}|) + \delta_{is} \ln h_{i,t-1}\} \right] D_{is,t} \qquad i = 1, \dots, N \tag{5}$$

where $D_{is,t}$ is a dummy variable indicating the day $s (s = 1, 2, 3, 4, 5, 6, 7)$ for asset i. The EGARCH volatility model is adopted to allow for leverage effect (typical for equity returns) and recently found for cryptocurrencies (Hafner, 2018).

Extending the Generalized DCC of Cappiello et al. (2006), Osborn et al. (2008) allow for periodic effects in the conditional correlations:

$$Q_t = \sum_{s=1}^{7} \left[C_s + A_s v_{t-1} v'_{t-1} A_s + B_s Q_{t-1} B_s \right] D_{s,t} \tag{6}$$

$$R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1} \tag{7}$$

where C_s is an $n \times n$ symmetric matrix of constants, $A_s = diag(\alpha_{s1}, \dots, \alpha_{sN})$ is a parameter diagonal matrix (the implied news parameters are $\alpha_{si}\alpha_{sj}$ for $i \neq j$ for day s), while $B_s = diag(\beta_{s1}, \dots, \beta_{sN})$ is a parameter diagonal matrix (the implied decay parameters are $\beta_{si}\beta_{sj}$ for $i \neq j$ for day s). As usual, we rescale the quantity Q_t in Eq. (6) to obtain a proper correlation matrix, with Q_t^* being a diagonal matrix composed of the square roots of the diagonal elements of Q_t.

We estimate the PG-DCC by quasi-maximum likelihood estimation (QMLE) dividing the estimation procedure into two separate estimations: the mean and volatility estimation first and then the correlation estimation (see Engle (2002), and Engle and Sheppard (2001), among many others)[1].

After estimation, our next step is to test for the following interesting hypothesis:

$$H_0 : A_s = A, B_s = B \qquad s = 1, 2, 3, 4, 5, 6, 7 \tag{8}$$

Hypothesis in Eq. (8) tests for whether there is seasonality in the news and decay parameters of the correlations.

3.1. Monte Carlo simulation

To show the finite sample properties of the proposed methodology, we conduct Monte Carlo simulations comparing the true values of the parameters to the estimated ones (mean and standard deviation values). For the simulations, 1000 samples of the model are obtained. Each sample includes 5 series of 2345 randomly generated returns drawn recursively from the correlation part of the model (PG-DCC in (6)) assuming a standard normal distribution. Fixed values for the parameters of the PG-DCC specification are used — see column 1 of Table 1.

The third and fourth columns of Table 1 report the arithmetic mean and standard deviation of the estimated values for the PG-DCC specification in the 1000 random samples, as well as the percentage of times the estimated parameters are statistically different from their theoretical values (column 2). Interestingly, the simulated values of the parameters are extremely close to their respective theoretical values, signaling the stability of the model.

[1] For details on the estimation of PG-DCC, we refer to Section 2.3 in Osborn et al. (2008).

Table 1
Numerical simulation of the PDCC model.

Parameter	True Value	Average	Avg. St. Dev.	% Rejected	Parameter	True Value	Average	Avg. St. Dev.	% Rejected
$A_{mon,1}$	0.100	0.111	0.096	0.059	$B_{mon,1}$	0.800	0.801	0.850	0.067
$A_{mon,2}$	0.100	0.080	0.101	0.052	$B_{mon,2}$	0.800	0.784	0.775	0.061
$A_{mon,3}$	0.100	0.114	0.091	0.038	$B_{mon,3}$	0.800	0.781	0.801	0.043
$A_{mon,4}$	0.100	0.109	0.096	0.051	$B_{mon,4}$	0.800	0.793	0.789	0.051
$A_{mon,5}$	0.100	0.101	0.108	0.030	$B_{mon,5}$	0.800	0.816	0.812	0.063
$A_{tue,1}$	0.050	0.031	0.049	0.051	$B_{tue,1}$	0.950	0.949	0.984	0.062
$A_{tue,2}$	0.050	0.034	0.017	0.069	$B_{tue,2}$	0.950	0.957	0.968	0.059
$A_{tue,3}$	0.050	0.061	0.097	0.042	$B_{tue,3}$	0.950	0.950	0.933	0.033
$A_{tue,4}$	0.050	0.034	0.074	0.058	$B_{tue,4}$	0.950	0.956	0.975	0.053
$A_{tue,5}$	0.050	0.052	0.012	0.068	$B_{tue,5}$	0.950	0.937	0.943	0.049
$A_{wed,1}$	0.150	0.142	0.175	0.055	$B_{wed,1}$	0.900	0.895	0.910	0.061
$A_{wed,2}$	0.150	0.135	0.125	0.069	$B_{wed,2}$	0.900	0.906	0.938	0.070
$A_{wed,3}$	0.150	0.140	0.105	0.034	$B_{wed,3}$	0.900	0.886	0.886	0.043
$A_{wed,4}$	0.150	0.153	0.202	0.060	$B_{wed,4}$	0.900	0.917	0.937	0.063
$A_{wed,5}$	0.150	0.133	0.151	0.036	$B_{wed,5}$	0.900	0.897	0.880	0.057
$A_{thu,1}$	0.080	0.086	0.051	0.054	$B_{thu,1}$	0.970	0.954	0.911	0.052
$A_{thu,2}$	0.080	0.084	0.085	0.068	$B_{thu,2}$	0.970	0.957	1.005	0.059
$A_{thu,3}$	0.080	0.090	0.133	0.031	$B_{thu,3}$	0.970	0.970	0.972	0.047
$A_{thu,4}$	0.080	0.068	0.035	0.063	$B_{thu,4}$	0.970	0.966	0.930	0.059
$A_{thu,5}$	0.080	0.076	0.085	0.067	$B_{thu,5}$	0.970	0.975	1.020	0.033
$A_{fri,1}$	0.030	0.041	0.037	0.065	$B_{fri,1}$	0.880	0.895	0.905	0.070
$A_{fri,2}$	0.030	0.010	−0.016	0.053	$B_{fri,2}$	0.880	0.885	0.848	0.062
$A_{fri,3}$	0.030	0.041	0.086	0.036	$B_{fri,3}$	0.880	0.865	0.882	0.034
$A_{fri,4}$	0.030	0.026	0.070	0.069	$B_{fri,4}$	0.880	0.866	0.841	0.055
$A_{fri,5}$	0.030	0.021	−0.012	0.047	$B_{fri,5}$	0.880	0.892	0.869	0.063
$A_{sat,1}$	0.100	0.096	0.111	0.053	$B_{sat,1}$	0.850	0.844	0.887	0.052
$A_{sat,2}$	0.100	0.116	0.131	0.064	$B_{sat,2}$	0.850	0.858	0.890	0.059
$A_{sat,3}$	0.100	0.092	0.055	0.033	$B_{sat,3}$	0.850	0.845	0.822	0.049
$A_{sat,4}$	0.100	0.101	0.104	0.051	$B_{sat,4}$	0.850	0.833	0.866	0.069
$A_{sat,5}$	0.100	0.112	0.096	0.064	$B_{sat,5}$	0.850	0.849	0.863	0.048
$A_{sun,1}$	0.030	0.039	0.038	0.060	$B_{sun,1}$	0.920	0.935	0.908	0.068
$A_{sun,2}$	0.030	0.026	0.037	0.060	$B_{sun,2}$	0.920	0.908	0.908	0.066
$A_{sun,3}$	0.030	0.021	0.037	0.044	$B_{sun,3}$	0.920	0.923	0.966	0.040
$A_{sun,4}$	0.030	0.039	0.018	0.053	$B_{sun,4}$	0.920	0.932	0.945	0.064
$A_{sun,5}$	0.030	0.013	0.055	0.048	$B_{sun,5}$	0.920	0.921	0.915	0.065

Notes: This table reports Monte Carlo simulation results for PDCC specification assuming 5 series that are normally distributed, based on 1000 randomly generated samples of 500 observations each. *Avg.* refers to the average value of the estimated parameters, *Avg. St. Dev.* to the average standard deviation of the estimated parameters, and *% Rejected* to the test whether the difference between the estimated parameter from its true value is significant or not.

4. Empirical analysis

4.1. Data

We use daily price data of Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Monero (XMR), and Stellar (XLM). Cryptocurrency data are obtained from https://coinmarketcap.com/ The period under examination goes from 10/08/2015 to 09/01/2022. We show in Table 2 the descriptive statistics of daily logarithmic returns of our data. These are broadly similar to those of other financial assets.

Online investor attention and sentiment are proxied by two previously published indices, both based on Google Trends. Google Trends Attention Index, proposed by Aslanidis et al. (2022), uses a selection of keywords to capture cryptocurrency market attention. The authors find this index to be informative for cryptocurrency returns and volatility. The Google Trends Sentiment Index, proposed by Liu and Tsyvinski (2021), is based on a combination of keywords that aims to capture positive versus negative sentiment towards the cryptocurrency market. Liu and Tsyvinski (2021) construct this index using weekly data for their study, while we reproduce it employing daily data for our sample period. For more details about the construction of these two indices, we refer to the aforementioned papers.

4.2. Results

Table 3 presents the estimated values of the mean and volatility parameters. First, cryptocurrencies exhibit a strong, positive, and statistically significant day-of-the-week effect, particularly on Fridays, and to a lesser extent on Thursdays, as measured by the μ parameter. The Friday effect echoes broad results in the literature on traditional markets (French, 1980; Gibbons and Hess, 1981; Keim and Stambaugh, 1984). This is in contrast to Caporale and Plastun (2019), who find a positive abnormal effect on Mondays for Bitcoin, but in a univariate framework. Second, particularly for smaller coins, there is evidence of mean reversion with negative ϕ parameter estimates, also over the weekends. This finding points to a not fully informationally efficient market, but with prices

Table 2
Descriptive statistics of daily returns.

	BTC	ETH	LTC	XLM	XMR
Observations	2345	2345	2345	2345	2345
Mean	0.0022	0.0036	0.0015	0.0020	0.0024
Median	0.0022	0.0007	0.0000	0.0002	0.0017
Min	−0.4799	−0.5695	−0.4662	−0.9097	−0.5322
Max	0.2276	0.4362	0.5524	1.0526	0.6426
Std. Deviation	0.0401	0.0617	0.0568	0.0895	0.0636
Skewness	−0.8067	−0.0354	0.5043	1.2380	0.4603
Kurtosis	14.6953	10.3821	15.4399	23.9251	15.6230
Jarque Bera	13 618.8430	5325.0798	15 219.8129	43 381.3963	15 651.7081

Table 3
Estimated PAR-PEGARCH model.

Parameter	BTC	ETH	LTC	XLM	XMR
μ_{Mon}	0.1790	0.3643	0.0481	−0.4295**	−0.1914
μ_{Tue}	−0.0845	0.1069	0.0225	−0.5284*	0.2182
μ_{Wed}	0.0508	−0.1865	−0.0268	−0.1431	−0.1723
μ_{Thu}	0.3597**	0.2023	0.5823**	−0.4846**	0.2440
μ_{Fri}	0.4125***	0.6923***	0.2840*	0.6548***	0.6444***
μ_{Sat}	0.0065	0.2646	0.1829	−0.4139*	0.3403*
μ_{Sun}	0.3467*	−0.0578	−0.2701	0.1007	0.5007*
ϕ_{Mon}	0.0602	0.0521	0.1779***	−0.1246**	0.0993*
ϕ_{Tue}	−0.0418	0.0016	−0.1193**	0.0292	−0.1614***
ϕ_{Wed}	0.0354	0.0006	0.0047	−0.2612***	−0.1852***
ϕ_{Thu}	−0.1363**	−0.1092*	−0.1339***	−0.2426***	−0.1760***
ϕ_{Fri}	−0.0676	−0.0493	−0.0312	−0.0667	−0.0168
ϕ_{Sat}	−0.2168***	−0.1448	−0.1375**	−0.0653	−0.2444***
ϕ_{Sun}	−0.1390	−0.1275	−0.1958***	−0.4094***	−0.2118***
ω_{Mon}	−0.4945	−0.7695	2.4856***	2.7159***	0.2670
ω_{Tue}	0.2545	1.2315*	−1.4569**	−8.5784***	0.4491
ω_{Wed}	0.0280	−2.8674	−1.9426***	0.7586***	−0.4869
ω_{Thu}	0.0734	0.9381	0.4811**	−0.0784	−0.6946*
ω_{Fri}	0.8004	0.8884	0.5135***	1.4427***	1.5851***
ω_{Sat}	1.3231*	1.1708*	−0.0135	−0.8823**	−0.1779
ω_{Sun}	−2.2962	−0.2759	−1.2192***	1.7291	0.2144
γ_{Mon}	−0.0008	0.0119	−0.0003	−0.0793	−0.0629**
γ_{Tue}	0.0833	0.0775	0.0935***	0.1509	0.1682***
γ_{Wed}	0.0496	−0.0089	0.1338***	−0.1304	0.0983***
γ_{Thu}	0.0610	0.0165	−0.0113	0.1186	0.1893***
γ_{Fri}	−0.0489	0.0209	0.0608***	0.2305	0.0032
γ_{Sat}	−0.0872*	−0.0374	−0.0437*	−0.1851	0.0103
γ_{Sun}	−0.0003	−0.0162	−0.0467*	−0.0846	−0.0329
θ_{Mon}	0.5068***	0.3651***	0.0995***	0.0244	0.1173***
θ_{Tue}	0.1333	0.1483	0.0677***	0.4947	0.1627***
θ_{Wed}	0.3637***	0.2561**	0.2397***	0.8418	0.2488***
θ_{Thu}	0.3411***	0.2562**	0.1923***	0.5395	0.4145***
θ_{Fri}	0.3778***	0.5644***	0.1336***	0.3027	0.1462***
θ_{Sat}	0.0938	0.2050**	0.1699***	0.7755	0.4387***
θ_{Sun}	0.0321	0.0951	0.1928***	0.7480	0.0516
δ_{Mon}	1.2609***	1.2596***	0.3862***	0.3858	0.9593***
δ_{Tue}	0.7868***	0.5897***	1.2618***	2.9710	0.7576***
δ_{Wed}	0.8690***	1.7375***	1.4517***	0.6948	1.1234***
δ_{Thu}	0.9627***	0.7473***	0.8116***	1.0291	1.2249***
δ_{Fri}	0.8903***	0.8416***	0.9972***	0.7649	0.6878***
δ_{Sat}	0.5214**	0.6978***	0.9975***	1.2265	0.9867***
δ_{Sun}	1.8609*	1.0614***	1.4416***	0.5940	0.9844***

reverting to their mean values. The mean reversion observed over the weekends suggests that investors gather information and actively trade in the market. This might explain the absence of the so-called "Monday effect" as observed in traditional markets. We also find, in line with Urquhart (2016) and Aharon and Qadan (2019), that volatility is highly persistent. Moreover, volatility tends to be higher on Fridays (mainly, for smaller coins), which is in accord with the positive Friday effect on returns. That is, for the smaller coins, higher returns go hand in hand with higher volatility, which confirms the positive risk-return relationship.

Another result drawn from Table 3 is that the leverage effect is widespread over the whole week, except for XLM. The leverage effect implies that negative shocks affect volatility more than positive shocks.

Turning to the correlations, one of the main findings in the literature is that correlations between cryptocurrencies and traditional assets are generally low, while cross-correlations between cryptocurrencies are often quite high (Corbet et al., 2018; Aslanidis et al.,

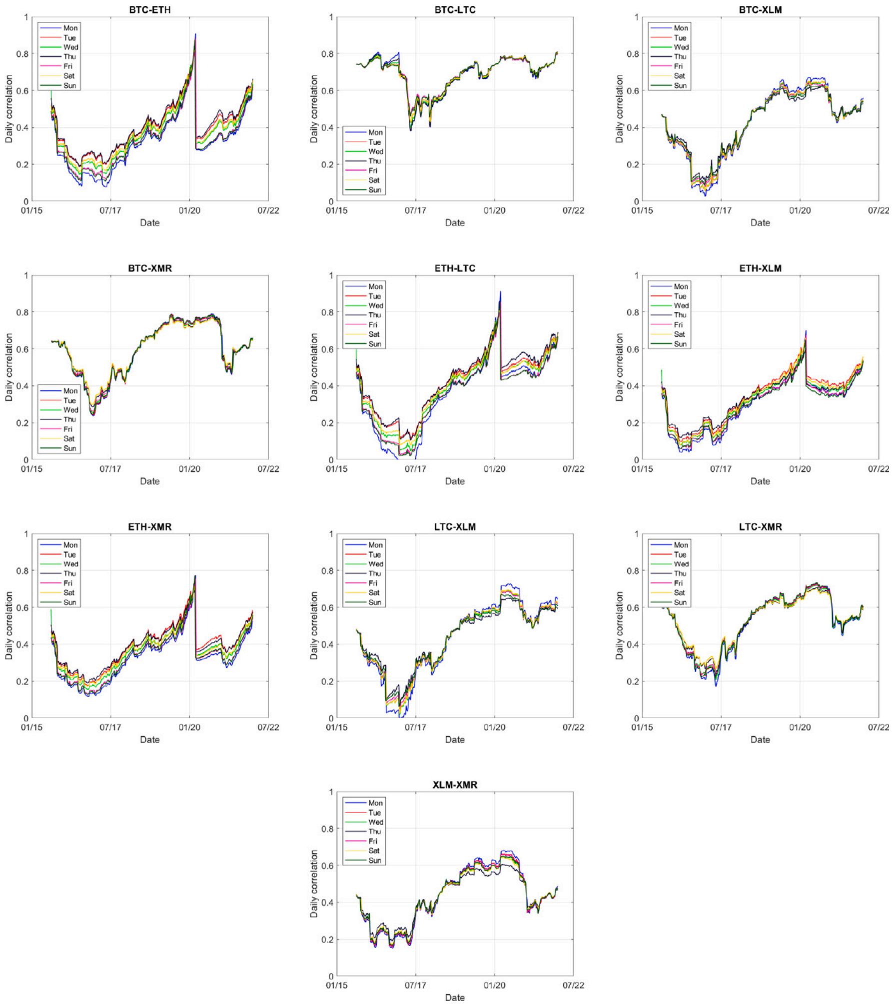

Fig. 1. Daily correlations.

2021). Taking this line of research a step further, we explore daily seasonality in the cross-correlations between cryptocurrencies in a versatile econometric framework and, more importantly, concerning online market attention and sentiment. Fig. 1 plots the correlation pairs for the seven days of the week. Some general patterns emerge from a visual examination of the plots. First, correlations differ across the week, except for the COVID-19 outbreak period, during which they become very similar. This may signal herd behavior patterns at the beginning of the health crisis. Second, correlations after 2017 experience a strong and sustained surge until about the onset of the COVID-19 pandemic. The estimates point to increases from around 10% to around 80%. Third, after the COVID-19 outbreak, cryptocurrency correlations exhibit seasonality again. That is, correlation pairs involving Ethereum show a dramatic fall in March 2020, whereas the remaining pairs maintain high levels until about early 2021. These findings suggest the distinct dynamic behavior of Ethereum compared to other cryptocurrencies. Towards the end of the sample, all correlations start to pick up again, reaching levels of around 60%. Overall, the seasonality in correlations is statistically significant (the null hypothesis in Eq. (8) is rejected at the 1% significance level).

To investigate the influence of online attention/sentiment on the cross-correlations, we adopt a quantile regression approach. Quantile regressions can be a useful tool in risk modeling, providing significant insights into the empirical analysis in finance. For instance, the quantile model allows for a heterogeneous impact, providing a more comprehensive picture of the effect of attention/sentiment on the entire distribution of the correlations, as opposed to standard linear regressions. Moreover, the quantile method is less sensitive to outliers and makes no assumptions about the data's distribution. These are important advantages in the context of financial data.

The quantile regression under study takes the following form:

$$corr_t = \sum_{s=1}^{7} \delta_{s,\tau} D_{s,\tau} + \beta_\tau \{Attention \text{ OR } Sentiment\}_t + \varepsilon_{\tau,t} \quad \tau \in (0,1) \tag{9}$$

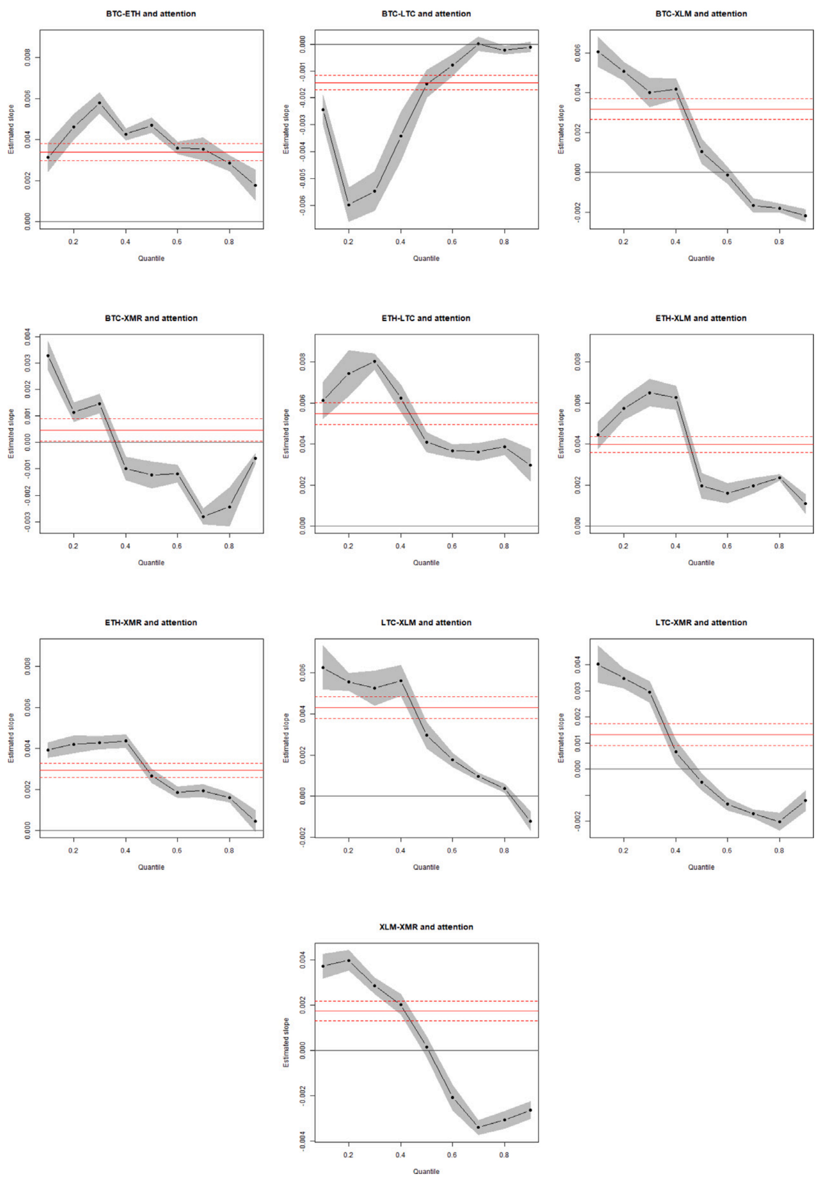

Fig. 2. Quantile regression between cryptocurrency cross-correlations and the index of Google Trends Attention. Gray areas indicate the 95% confidence interval.

where $corr_t$ refers to the cross correlations obtained from the PG-DCC, while $\{Attention \text{ OR } Sentiment\}_t$ is the indicator of interest.

Next, we plot the estimated attention and sentiment coefficients across the different quantiles in Fig. 2 and Fig. 3, respectively. There are four main takeaways from these plots. First, the effect of sentiment is largely negative with attention exerting a positive effect on the cross-correlations. This result was not unexpected given that the correlation coefficient between market attention and sentiment is estimated at −21%. Second, across all quantiles, sentiment has a larger impact than attention (approximately 10 times larger!). These findings imply that attention appears to be a rough proxy for investors' interest, with sentiment being a more elaborate expression of investors' attitudes towards the market. Third, attention has a more pronounced effect at the lower quantiles (in the range of $\tau \in (0.2, 0.4)$) than at the higher ones, except for the BTC-LTC pair. Fourth, a U-shaped sentiment-return relationship is generally observed, where sentiment has a stronger (negative) effect in the middle quantiles and weaker in the more extreme quantiles. Consequently, our results show that the effect of attention is larger when cryptocurrency correlations are extreme (either strongly positive or strongly negative), whereas the effect of sentiment becomes more important for mild correlations.

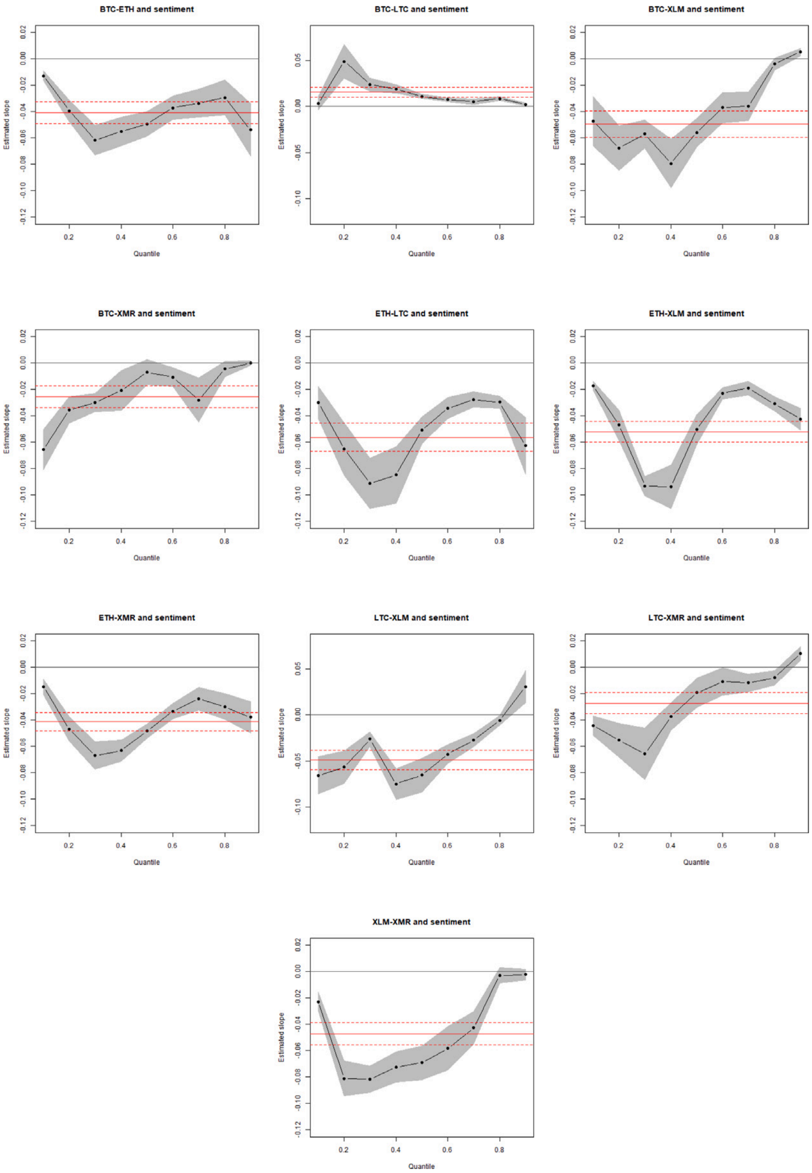

Fig. 3. Quantile regression between cryptocurrency cross-correlations and the index of Google Trends Sentiment. Gray areas indicate the 95% confidence interval.

5. Conclusions

Examining cryptocurrency cross-correlations can be crucial for academics, regulators, and policymakers. Although research on cryptocurrencies is fast-growing, the existing literature lacks a comprehensive, yet flexible, framework to account for seasonality and time-variation in the cross-correlations, as well as in the returns and volatilities. Precisely, the current paper fills this gap and goes one step further by studying the link between these correlations and online market attention and sentiment.

Based on the Periodic Generalized Dynamic Conditional Correlation methodology by Osborn et al. (2008), our results provide further insights into the existence of the day-of-the-week effect on cryptocurrencies.

In addition to seasonality in returns and volatility, we provide new evidence on the cross-correlations among cryptocurrencies. We report a general and significant decrease in all of them between 2015 and 2017 and a subsequent increase in the correlations up until the COVID-19 outbreak. Furthermore, while correlations appear to be different across the week during most of the period, they converge around March-April 2020, reflecting the panic in the markets over several weeks.

A further interesting outcome of the results is related to the effect of investor attention and sentiment. Investor attention turns out to have a positive, albeit small, effect on the correlations. On the contrary, investor sentiment has a negative and approximately ten times stronger impact on the correlations. The substantial disparity in the magnitudes of these estimates may suggest that online sentiment serves as a more refined and elaborate indicator of investors' beliefs and emotions compared to online attention, which might function as a preliminary gauge of interest in cryptocurrency markets.

On the other hand, the negative estimates of sentiment imply that when economic agents become optimistic (towards the cryptocurrency market), they are willing to invest in alternative cryptocurrencies. As a consequence, correlations drop, increasing portfolio diversification benefits. Instead, when sentiment is low, economic agents perceive little difference across cryptocurrencies, and their correlations increase.

One of the limitations of our paper is the measurement of attention and sentiment. Although both indices are based on the same source of data (Google Trends), there are alternative indices based on newspapers (Sapkota, 2022), Twitter (Shen et al., 2019) and blogs (Low et al., 2024). Future research could explore the implications of the results for portfolio construction and hedging analysis. In particular, we aim to use the PG-DCC model in a portfolio evaluation exercise, with different weighting methods, such as equally weighted, minimum variance, and hedging portfolios.

CRediT authorship contribution statement

Nektarios Aslanidis: Writing – original draft, Writing – review & editing, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Aurelio F. Bariviera:** Writing – original draft, Writing – review & editing, Investigation, Formal analysis, Data curation, Conceptualization. **Christos S. Savva:** Writing – original draft, Writing – review & editing, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

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References

Admati, A.R., Pfleiderer, P., 1988. A theory of intraday patterns: Volume and price variability. Rev. Financ. Stud. 1 (1), 3–40.
Agoraki, M.-E.K., Aslanidis, N., Kouretas, G.P., 2022. U.S. banks' lending, financial stability, and text-based sentiment analysis. J. Econ. Behav. Organ. 197, 73–90.
Aharon, D., Qadan, M., 2019. Bitcoin and the day-of-the-week effect. Finance Res. Lett. 31, 415–424.
Akyildirim, E., Aysan, A.F., Cepni, O., Darendeli, S.P.C., 2021. Do investor sentiments drive cryptocurrency prices? Econom. Lett. 206, 109980.
Alexander, G.J., Ferri, M.G., 2000. Day-of-the-week patterns in volume and prices of nasdaq high-yield bonds. J. Portf. Manag. 26 (3), 33–41.
Aslanidis, N., Bariviera, A.F., López, Óscar G., 2022. The link between cryptocurrencies and google trends attention. Finance Res. Lett. 47, 102654.
Aslanidis, N., Bariviera, A.F., Martinez-Ibañez, O., 2019. An analysis of cryptocurrencies conditional cross correlations. Finance Res. Lett. 31, 130–137.
Aslanidis, N., Bariviera, A.F., Perez-Laborda, A., 2021. Are cryptocurrencies becoming more interconnected? Econom. Lett. 199, 109725.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61 (4), 1645–1680.
Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment1we are grateful to the NSF for financial support, and to Oliver Blanchard, Alon Brav, John Campbell (a referee), John Cochrane, Edward Glaeser, J.B. Heaton, Danny Kahneman, David Laibson, Owen Lamont, Drazen Prelec, Jay Ritte. J. Financ. Econ. 49 (3), 307–343.
Bariviera, A.F., 2017. The inefficiency of bitcoin revisited: A dynamic approach. Econom. Lett. 161, 1–4.
Bindseil, U., Schaaf, J., 2024. ETF approval for bitcoin – the naked emperor's new clothes. https://www.ecb.europa.eu/press/blog/date/2024/html/ecb.blog202402220929f86e23.en.html. (Accessed 02 July 2024).
Borri, N., 2019. Conditional tail-risk in cryptocurrency markets. J. Empir. Financ. 50, 1–19.
Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.I., 2017. On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? Finance Res. Lett. 20, 192–198.
Buffett, W., 2018. Warren buffett explains one thing people still don't understand about bitcoinn. https://www.cnbc.com/2018/05/01/warren-buffett-bitcoin-isnt-an-investment.html. Accessed 04 March 2020.
Caporale, G., Plastun, A., 2019. The day of the week effect in the cryptocurrency market. Finance Res. Lett. 31, 258–269.
Cappiello, L., Engle, R.F., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. J. Financ. Econom. 4 (4), 537–572.
Cheah, E.-T., Fry, J., 2015. Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. Econom. Lett. 130, 32–36.
Chen, Z., Lien, D., Lin, Y., 2021. Sentiment: The bridge between financial markets and macroeconomy. J. Econ. Behav. Organ. 188, 1177–1190.
Condoyanni, L., O'Hanlon, J., Ward, C., 1987. Day of the week effects on stock returns: International evidence. J. Bus. Finance Account. 14 (2), 159–174.
Cong, L.W., Li, Y., Wang, N., 2021. Tokenomics: Dynamic adoption and valuation. Rev. Financ. Stud. 34.
Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L., 2019. Cryptocurrencies as a financial asset: A systematic analysis. Int. Rev. Financ. Anal. 62 (2018), 182–199.
Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econom. Lett. 165, 28–34.
Cross, F., 1973. The behavior of stock prices on fridays and mondays. Financ. Anal. J. 29 (67).
Dias, I.K., Fernando, J.R., Fernando, P.N.D., 2022. Does investor sentiment predict bitcoin return and volatility? a quantile regression approach. Int. Rev. Financ. Anal. 84, 102383.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.
Donier, J., Bouchaud, J.-P., 2015. Why do markets crash? bitcoin data offers unprecedented insights. PLoS One 10 (10), 1–11.
Engle, R., 2002. Dynamic conditional correlation. J. Bus. Econom. Statist. 20 (3), 339–350.
Engle, R.F., Sheppard, K., 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. NBER Working Papers 8554, National Bureau of Economic Research, Inc.
Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. J. Finance 25 (2), 383–417, Papers and Proceedings of the Twenty-Eighth Annual Meeting of the American Finance Association New York, N.Y. December, (1969) 28-30.

Fama, E., 2015. Nobel prize winner Eugene Fama on bitcoin. https://cointelegraph.com/news/nobel-prize-winner-eugene-fama-on-bitcoin. Accessed 04 March 2020.
Fields, M.J., 1931. Stock prices: A problem in verification. J. Bus. Univ. Chicago 4 (4), 415–418.
Fields, M.J., 1934. Security prices and stock exchange holidays in relation to short selling. J. Bus. Univ. Chicago 7 (4), 328–338.
French, K.R., 1980. Stock returns and the weekend effect. J. Financ. Econ. 8 (1), 55–69.
García, D., 2013. Sentiment during recessions. J. Finance 68 (3), 1267–1300.
Gibbons, M.R., Hess, P., 1981. Day of the week effects and asset returns. J. Bus. 54 (4), 579–596.
Guégan, D., Renault, T., 2021. Does investor sentiment on social media provide robust information for bitcoin returns predictability? Finance Res. Lett. 38, 101494.
Hafner, C.M., 2018. Testing for bubbles in cryptocurrencies with time-varying volatility. J. Financ. Econom..
Jiao, P., Veiga, A., Walther, A., 2020. Social media, news media and the stock market. J. Econ. Behav. Organ. 176, 63–90.
Keim, D.B., Stambaugh, R.F., 1984. A further investigation of the weekend effect in stock returns. J. Finance 39 (3), 819–835.
Kinateder, H., Papavassiliou, V.G., 2019. Calendar effects in bitcoin returns and volatility. Finance Res. Lett. 101420.
Lakonishok, J., Levi, M., 1982. Weekend effects on stock returns: A note. J. Finance 37 (3), 883–889.
Lakonishok, J., Maberly, E., 1990. The weekend effect: Trading patterns of individual and institutional investors. J. Finance 45 (1), 231–243.
Li, Y., Goodell, J.W., Shen, D., 2021. Comparing search-engine and social-media attentions in finance research: Evidence from cryptocurrencies. Int. Rev. Econ. Finance 75, 723–746.
Li, L., Miu, P., 2023. Are cryptocurrencies a safe haven for stock investors? A regime-switching approach. J. Empir. Financ. 70, 367–385.
Liu, Y., Tsyvinski, A., 2021. Risks and returns of cryptocurrency. Rev. Financ. Stud. 34 (6), 2689–2727.
Liu, Y., Tsyvinski, A., Wu, X.I., 2022. Common risk factors in cryptocurrency. J. Finance 77, 1133–1177. http://dx.doi.org/10.1111/jofi.13119.
Low, J.M., Tan, Z.J., Tang, T.Y., Salleh, N.M., 2024. Deep learning and sentiment analysis-based cryptocurrency price prediction. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 14322 LNCS, pp. 40–51.
Lucey, B.M., Vigne, S.A., Yarovaya, L., Wang, Y., 2022. The cryptocurrency uncertainty index. Finance Res. Lett. 45.
Ma, D., Tanizaki, H., 2019. The day-of-the-week effect on bitcoin return and volatility. Res. Int. Bus. Finance 49, 127–136.
Manela, A., Moreira, A., 2017. News implied volatility and disaster concerns. J. Financ. Econ. 123 (1), 137–162.
Mbanga, C., 2019. The day-of-the-week pattern of price clustering in bitcoin. Appl. Econ. Lett. 26 (10), 807–811.
Merediz-Solà, I., Bariviera, A.F., 2019. A bibliometric analysis of bitcoin scientific production. Res. Int. Bus. Finance 50, 294–305.
Nadarajah, S., Chu, J., 2017. On the inefficiency of bitcoin. Econom. Lett. 150, 6–9.
Narayanasamy, A., Panta, H., Agarwal, R., 2023. Relations among bitcoin futures, bitcoin spot, investor attention, and sentiment. J. Risk Financial Manag. 16 (11).
Osborn, D.R., Savva, C.S., Gill, L., 2008. Periodic dynamic conditional correlations between stock markets in europe and the us. J. Financ. Econom. 6 (3), 307–325.
Ross, S.A., 2005. Neoclassical Finance. Princeton University Press, Princeton(NJ).
Sapkota, N., 2022. News-based sentiment and bitcoin volatility. Int. Rev. Financ. Anal. 82, 102183.
Shen, D., Urquhart, A., Wang, P., 2019. Does twitter predict bitcoin? Econom. Lett. 174, 118–122.
Shi, G., Goodell, J.W., Shen, D., 2024. Investor attention and gamefi returns: A transfer entropy analysis. Finance Res. Lett. 61, 105047.
Shiller, R.J., 2015. Irrational Exuberance: Revised and Expanded Third Edition, third ed. Princeton University Press, Princeton (NJ).
Shiller, R.J., 2017. Narrative economics. Amer. Econ. Rev. 107 (4), 967–1004.
Siganos, A., Vagenas-Nanos, E., Verwijmeren, P., 2014. Facebook's daily sentiment and international stock markets. J. Econ. Behav. Organ. 107 (PB), 730–743.
Smales, L., 2022. Investor attention in cryptocurrency markets. Int. Rev. Financ. Anal. 79, 101972.
Sockin, M., Xiong, W., 2023. A model of cryptocurrencies. Manage. Sci..
Tetlock, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. J. Finance 62 (3), 1139–1168.
Urquhart, A., 2016. The inefficiency of bitcoin. Econom. Lett. 148, 80–82.
Urquhart, A., 2018. What causes the attention of bitcoin? Econom. Lett. 166, 40–44.