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Weekly dynamic conditional correlations among cryptocurrencies and traditional assets

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Abstract

This paper adopts a versatile multivariate conditional correlation model to estimate daily seasonality in the returns, the volatility, and the correlations between stocks, bonds, gold and Bitcoin. Besides the well known seasonality in stocks and bonds, the day-of-the-week effect is also present in Bitcoin. Mondays are associated with higher Bitcoin returns, while Wednesdays with higher Bitcoin volatility. As opposed to previous literature, our results indicate strong evidence of Bitcoin's leverage effect. Moreover, we show that daily correlations between Bitcoin and traditional assets are higher at the beginning of the week, while the volatility of these correlations decreases over the week. Our results offer interesting insights in terms of investment and portfolio diversification, that can be applied to the analysis of systematic risk asset allocation and hedging.
Keywords: Day-of-the-week effect; dynamic conditional correlation; Bitcoin; volatility seasonality
JEL codes: G01; G10; G12; G22

1 Introduction

A white paper authored under the pseudonym "Nakamoto" and posted on the web, set the foundations of a new paradigm in information validation (Nakamoto, 2009). It broke the common wisdom that a validation authority must be a central node of a network, and expanded the validation responsibility to several members of such network. Such decentralized validation is the core of this new technology called "blockchain". The original aim of Nakamoto's proposal was

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to set a peer-to-peer electronic payment system that could be alternative to traditional banking. We should bring to memory that in 2008 took place one of the most serious financial crises in modern times (Almunia et al., 2009). Public opinion regarding banks were at historical lows, so Nakamoto's creation was consistent with the moods of times. As a by-product of blockchain technology, emerged Bitcoin, as the first money not issued by a nation state nor, by one particular private individual. Actually Bitcoin is minted according to fixed rules that are related to the very Bitcoin network activity. Bitcoin's enormous success encouraged individuals to create other blockchain networks and produce additional cryptocurrencies. As of January 2020, there are more than 5000 cryptocurrencies and tokens, traded in 20000 online venues, with a total market capitalization of 217 billions, and daily transactions exceeding 77 billions (Coinmarket, 2020). Despite the large number of cryptocoins, Bitcoin constitutes around 68% of the market, and according to Bariviera et al. (2018) most studies focus their attention on Bitcoin, rather than on the other cryptocurrencies.

In recent years, there has emerged a burgeoning academic literature on cryptocurrencies. There are many interesting aspects in the analysis of cryptocurrencies. Initially, the study of cryptocurrencies was from a technological point of view. In this sense, early papers were more focused on the computer science aspects, in order to understand how blockchain worked (Zyskind et al., 2015). Later on, the economic literature was more conceptual, aimed at discerning, from a monetary point of view, the potential of Bitcoin as a substitute of fiat currencies (Yermack, 2013; Böhme et al., 2015). Recently, the classical financial economics questions such as informational efficiency and long range memory are also tested for Bitcoin.

Two related topics have emerged in the literature: (a) Bitcoin's diversification potential (Liu, 2018; Platanakis and Urquhart, 2019; Aslanidis et al., 2019); (b) daily seasonality in Bitcoin markets (Mbanga, 2019; Ma and Tanizaki, 2019; Caporale and Plastun, 2019; Aharon and Qadan, 2019). Considering the growing interest of the financial industry to provide cryptocurrency related products, such as exchange traded funds, mutual or hybrid funds, we consider that it is relevant to address both issues together.

The aim of the current paper is to explore, in a unified framework, the presence of daily seasonality in Bitcoin returns and volatility, and, more importantly, in its correlations with traditional assets. Consequently, we offer useful insights for both academics and practitioners. From a practitioner's point of view, studying the financial and statistical properties of Bitcoin can provide hints to design products and innovative investment strategies. The Bitcoin market gives the opportunity to study the behavior of a *pure* speculative asset. Fama (2015), major fund managers (Buffett, 2018), and academic research (Cheah and Fry, 2015) argue that the fundamental value of Bitcoin is close to zero.

From an academic point of view, the current paper contributes to the literature as follows: (i) we revisit the day-of-the-week effect on returns and volatility, while offering new evidence of day-of-the-week effect for the correlations between stocks, bonds, gold and Bitcoin. (ii) unlike previous studies, we examine seasonality in assets returns considering a more versatile multivariate volatility framework; (iii) more importantly and to the best of our knowledge, we are the first to document substantial day-of-the-week effect in Bitcoin correlations with traditional assets, and a decline in correlation volatility over the week.

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 the main findings of our study. Finally, Section 5 draws the main conclusions.

2 Literature review

In this section, we will focus exclusively in the closest research lines related to our paper. For a full landscape of Bitcoin literature, we refer to Corbet et al. (2019) and Merediz-Solà and Bariviera (2019), who undertake comprehensive reviews in this field.

2.1 The Efficient Market Hypothesis

The traditional definition of informational efficiency is in 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 white noise. The Efficient Market Hypothesis (EMH) is a necessary 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.

Early literature on cryptocurrencies was mainly devoted to test the 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 show evidence of initial information inefficiency in the Bitcoin market. However, the market seems to increase its level of informational efficiency over time. Nadarajah and Chu (2017) reexamines Urquhart (2016) using power transformations of daily returns, without rejecting the null hypothesis of informational efficiency. Bouri et al. (2017a) study Bitcoin's return-volatility behavior before and after the severe market crash of 2013, and show evidence of serial autocorrelation in Bitcoin returns. Bouri et al. (2017b) scrutinize the hedge and safe haven properties of Bitcoin *vis-à-vis* international stock and bond indices and several currencies. The main finding is that Bitcoin proves useful as a diversifier rather than as a hedge instrument. Finally, Balcilar et al. (2017) detect nonlinearities in the return-volume relationship, which allows for return prediction.

Furthermore, Bariviera (2017) documents that the Bitcoin market exhibits time-varying increasing information efficiency and persistence in volatility. The policy implication here is that the market becomes prone to large swings (either positive or negative ones). Taking this into account, Donier and Bouchaud (2015) study different measures of liquidity as early warning signs of Bitcoin market crash.

2.2 Assets correlation and portfolio optimization

One key aspect in portfolio theory, and broadly in financial economics, is the correct assessment of correlation returns among different assets. Such 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 cryptocurencies (Bitcoin, Ripple, Litecoin) are rather isolated from other assets such as gold, stocks or bonds, offering diversification opportunities to investors.

Another closely related paper is Zhang et al. (2018) who construct a cryptocurrency composite index (CCI) to study the relation between this index and Dow Jones Industrial Average (DJIA). In a similar vein, Trimborn and Härdle (2018) construct a cryptocurrency index which reacts to market structure changes, considering that one of the characteristics of this market is the frequent emergence and disappearance of cryptocurrencies. Smales (2019) considers a portfolio of Bitcoin and traditional assets to assess the safe haven properties of Bitcoin, but based on unconditional correlations. Instead, Aslanidis et al. (2019) model the conditional correlations directly. Other related studies include Dyhrberg (2016), Klein et al. (2018), Katsiampa (2019), among others.

Recently, Borri (2019) finds that cryptocurrencies are highly exposed to tail-risk within cryptomarkets, while they are not exposed to tail-risk with respect to traditional assets, such as U.S. stocks or gold.

2.3 Day-of-the-week effect

Daily and monthly seasonality are recurring topics in financial economics. The anomalous behavior (positive or negative) of the returns on a particular day is described under the generic name of the day-of-the-week effect. The existence of this anomaly is based on the assumption that returns should be equal across the week. The origins of this effect can be traced back to Fields (1931, 1934), who investigate the propensity of the operators to sell on the last day of negotiation in order not to carry with the uncertainty over the weekend or holiday. Research on daily seasonality studies begins to gain momentum in the 1970s and 1980s. Cross (1973) documents abnormal distributions of returns on Monday and Friday in the US market. Subsequently, French (1980) reexamine the US makret and divide the effect into Monday effect (which refers to the fact that this day has a negative return) and Friday effect (abnormal and significantly high return on this day). Condoyanni et al. (1987) extend the study of the weekend effect to the markets of the United States, Canada, United Kingdom, France, Australia, Japan and Singapore for the period 1969-1984. Jaffe et al. (1989) found that Monday's returns are significantly lower when the market has fallen the previous week than when it has risen. Lauterbach and Ungar (1992) study the Israeli market. A distinctive fact of this market is that it operates from Sunday to Thursday. In their study (from 02/01/1977 to 01/02/1991), it is observed that Sunday (first day of operation after the weekend) registers the highest performance. In turn, Monday and Tuesday, are the days of lowest returns Regarding bond markets, Alexander and Ferri (2000) finds patterns of daily seasonality in high yield corporate bonds.

There are several competing explanations to such abnormal behavior, but none is completely satisfactory. Lakonishok and Levi (1982) give a partial explanation to this effect, based on the delays in transactions settlement 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 of behavior of individual and institutional investors. According to their study, individuals tend to operate more on Mondays, especially to carry out sales operations. Admati and Pfleiderer (1988) indicate that the day of the week effect could be caused by the interaction between informed operators (with insider information) and liquidity operators. Theobald and Price (1984) find that, in the British market, Monday effect is greater for thin traded stocks. There are other attempts of explanations, but it is still an open issue in financial economics.

In the case of cryptocurrencies, daily seasonality is a stronger puzzle, because there is no market closings, nor holidays, and non homogeneous institutional agreements. Studies conducted so far, have been based on univariate models, mainly focused only on cryptocurrencies. 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) shows evidence of a Wednesday effect in mean returns. Finally, Aharon and Qadan (2019) reports day-of-the-week effect on Bitcoin at both return and variance.

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 cryptocurrencies and traditional assets. 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.

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

$$y_t = \sum_{s=1}^{5} \left[\mu_s + \sum_{l=1}^{p} \phi_{ls} y_{t-l} \right] D_{s,t} + \varepsilon_t, \qquad t = 1, \ldots, T \tag{1}$$

where the scalar $D_{s,t}$ is a dummy variable indicating the day of the week s ($s = 1, 2, 3, 4, 5$), while p ($p = 1, \ldots, 5$) is the order of the autoregression. The conditional covariances of the shocks in Equation 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 $D_t \equiv diag\left(\sqrt{h_{1,t}}, ..., \sqrt{h_{N,t}}\right)$ 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 $\rho_{ii,t} = 1, i = 1, \ldots, N$ and $t = 1, \ldots, T$. Each of the univariate error processes follows a periodic EGARCH$(1, 1)$ specification:

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

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

where $D_{is,t}$ is a dummy variable indicating the day $s(s = 1, 2, 3, 4, 5)$ 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:

$$Q_t = \sum_{s=1}^{5} \left[C_s + A_s\upsilon_{t-1}\upsilon'_{t-1}A_s + B_s Q_{t-1} B_s\right] D_{s,t} \tag{6}$$

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

where C_s is an $n \times n$ symmetric matrix of constants, $A_s = diag(\alpha_{s1}, \ldots, \alpha_{sN})$ is a parameter diagonal matrix (the implied news parameters are $\alpha_{si}\alpha_{sj}$ for $i \neq j$ for day s), while $B_s = diag(\beta_{s1}, \ldots, \beta_{sN})$ 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

Table 1: Descriptive statistics of daily returns

	Bitcoin	S&P500	BOND	GOLD
Observations	1283	1283	1283	1283
Mean	0.00174	0.00034	0.00001	-0.00001
Median	0.00176	0.00023	0	0
Std Deviation	0.04462	0.00825	0.00316	0.00787
Skewness	-0.15575	-0.45570	-0.07811	0.23168
Kurtosis	8.61111	7.15133	4.01433	5.80148
Jarque Bera	1688	965	56	431

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 hypotheses:

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

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

4 Empirical Analysis

4.1 Data

We use daily price data on Bitcoin (BTC), Standard & Poors 500 Composite (SP500), S&P US Treasury bond 7-10Y index (BOND), and Gold Bullion LBM (GOLD). Cryptocurrency data are obtained from https://coinmarketcap.com/, and for the other assets the data comes from Eikon Thomsom Reuters. The period under examination goes from 23/05/2014 to 24/04/2019. Cryptocurrencies are traded 24 hours a day, 7 days a week, while traditional assets are traded in organized markets that are open during the working days. Consequently, we adapt the Bitcoin sample to the sample availability of the traditional assets.

We show in Table 1 the descriptive statistics of daily logarithmic returns of Bitcoin and traditional assets.

4.2 Results

Table 2 presents the estimated values of the mean and volatility parameters. Bitcoin exhibits a strong and statistically significant Monday effect, with an intercept coefficient of 0.4768. This result is in line with Caporale and Plastun (2019), who also find a strong Monday effect for Bitcoin, but not for other cryptocurrencies. In contrast, Kinateder and Papavassiliou (2019) show a negative Wednesday effect using a different sample period.

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

Related to the more traditional literature on day-of-the week effect, our results generally echo previous findings in Jaffe et al. (1989) and Alexander and Ferri (2000), among others. For example, we find that bonds have the usual seasonality (statistically significant negative returns on Monday and positive returns on Friday), while stocks display day-of-the-week effect more on Wednesday and Friday. As for gold, there is little daily seasonality, with the intercept coefficients being statistically insignificant.

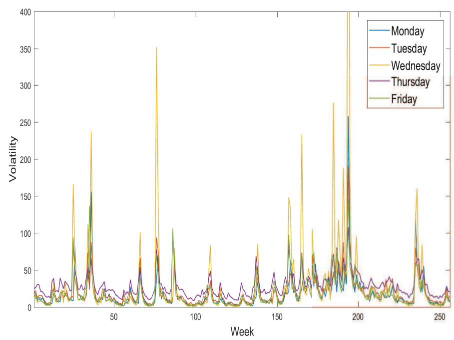
Turning to Bitcoin volatility, we report a strong Wednesday effect, with a significantly higher volatility, compared to the rest of the week. Aharon and Qadan (2019) also find support for seasonality in volatility, but on Mondays. The authors study investors' attention to Bitcoin as proxied by the Google Search Volume (GSV), and show that GSV is higher at the beginning of the week. Given that trading volume and investors' attention increase at the beginning of the week, this could explain the high price volatility we observe for Bitcoin.

Moreover, contrary to other studies (Ma and Tanizaki, 2019; Kinateder and Papavassiliou, 2019), we show strong evidence of Bitcoin's leverage effect, as indicated by the statistically significant θ parameter. This is a novel result and may reflect the high uncertainty surrounding this new market as opposed to more established financial markets, which makes investors more sensitive to negative news than to positive ones. For example, Figure 1 plots the estimated asset volatilities over the week. Note that Bitcoin exhibits substantially higher volatility than the traditional assets (more than 40 times higher!). As a result, investors are expected to be more risk averse in this market leading to a more pronounced leverage effect for Bitcoin than for the other assets (as observed in the magnitude of θ).

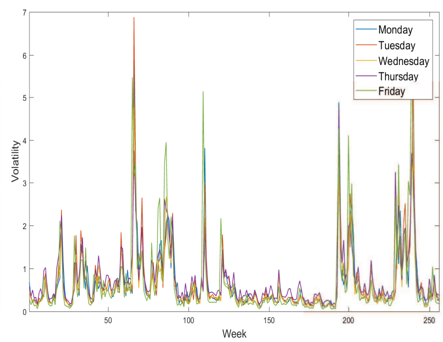
Another interesting result drawn from our study is the highly persistent volatility. This result corroborates previous findings in Urquhart (2016) and in Aharon and Qadan (2019), among others.

More recently, Aslanidis et al. (2019) explore the time-varying correlations between cryptocurrencies and traditional assets assuming constant correlation over the week. One of the authors' main findings is that the mean correlations of Bitcoin-stocks and of Bitcoin-bonds are 0.035 and -0.037, respectively. The current paper, however, uncovers some further interesting features about these correlations. Table 3 shows the mean of the estimated dynamic correlations for all asset pairs, while Figure 2 plots the estimated daily correlations between Bitcoin and the traditional assets. Given that the proposed periodic DCC model is a more flexible methodology, it allows for correlations to vary over the week. Although, in practice, we find low mean correlations of Bitcoin-stocks and of Bitcoin-bonds, these correlations are generally higher at the beginning of the week. This result can be confirmed by the test of Eq. (8), which shows that the null hypothesis of equal correlations over the week is rejected at any significance level (p-value=0.0000). Similarly to Corbet et al. (2018) and to Aslanidis et al. (2019), the correlations of Bitcoin-gold are admitted low compared to the other asset pairs.

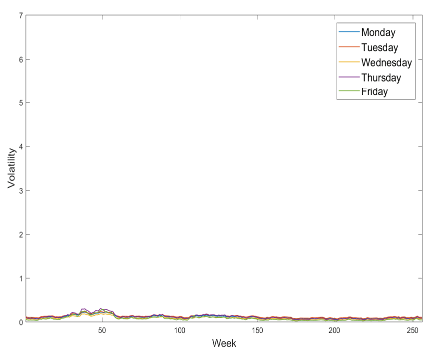
Another novelty of our analysis is the study of the volatility of daily corre-



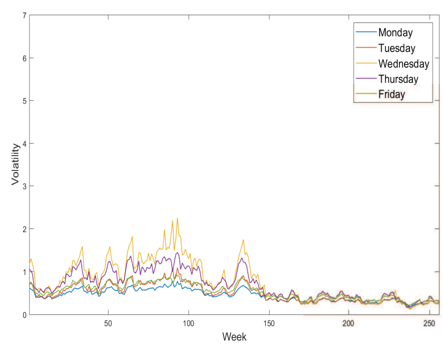
(a) Bitcoin



(b) S&P500



(c) Bonds



(d) Gold

Figure 1: Daily volatility

Table 2: Estimated PAR-PEGARCH model

Coefficient	Bitcoin	Bonds	sp500	Gold
β_{Mo}	0.4768^{***}	-0.0341^{***}	0.0086	0.0250
β_{Tu}	0.0502	-0.0016	-0.0013	-0.0487
β_{We}	-0.1265	0.0097	0.1070^{**}	0.0525
β_{Th}	0.2691	0.0053	-0.0017	-0.0210
β_{Fr}	0.3629	0.0328^{**}	0.1151^{***}	-0.0056
ϕ_{Mo}	-0.0343	-0.1281^{***}	0.0378	0.0681
ϕ_{Tu}	0.1633^{**}	-0.0001	-0.1056	0.0256
ϕ_{We}	-0.1178	0.0173	-0.0895	0.0413
ϕ_{Th}	0.1432^{**}	-0.0186	-0.0639	-0.0224
ϕ_{Fr}	-0.0432	-0.1516^{***}	-0.1271	-0.0275
ω_{Mo}	0.9408^{***}	-0.2217^{***}	-0.0189	0.4069^{***}
ω_{Tu}	-1.8418^{***}	0.1396	-0.1063	0.7073^{***}
ω_{We}	2.4492^{***}	0.9289^{***}	0.1715	-0.1507
ω_{Th}	-3.1250^{***}	0.3953^{**}	-0.2817	-0.3342^{***}
ω_{Fr}	0.1169	-0.8273^{***}	-0.0345	-0.2455^{***}
γ_{Mo}	0.0140	-0.0158	-0.2502^{***}	0.0235
γ_{Tu}	0.1591^{***}	-0.0165	-0.1850^{**}	0.0146
γ_{We}	-0.1258^{***}	-0.0318	-0.1591^{***}	-0.0527^{***}
γ_{Th}	0.0671	0.1212^{***}	-0.2852^{***}	-0.0279^{**}
γ_{Fr}	-0.1135^{**}	0.0030	-0.2321^{***}	0.0018
θ_{Mo}	0.3913^{***}	-0.0081	-0.0619	-0.0465^{**}
θ_{Tu}	0.6402^{***}	-0.0194	0.1782^{**}	0.0351
θ_{We}	0.1684^{***}	-0.0123	0.0420	-0.1250^{***}
θ_{Th}	0.3387^{***}	0.1075^{***}	0.3081^{***}	0.0029
θ_{Fr}	0.4449^{***}	-0.0952^{***}	0.2092^{**}	0.0477^{***}
δ_{Mo}	0.7365^{***}	0.8279^{***}	0.9823^{***}	1.3821^{***}
δ_{Tu}	1.6044^{***}	1.2617^{***}	0.9437^{***}	1.4585^{***}
δ_{We}	0.3427^{***}	1.2587^{***}	0.8492^{***}	0.7667^{***}
δ_{Th}	1.7431^{***}	1.4010^{***}	1.2653^{***}	0.6916^{***}
δ_{Fr}	0.9362^{***}	0.5300^{***}	0.7390^{***}	0.9246^{***}

Table 3: Mean dynamic correlations

Asset 1	Asset 2	Monday	Tuesday	Wednesday	Thursday	Friday
S&P500	Bitcoin	0.0801	0.0868	0.0647	0.0638	0.0744
	Bond	-0.1303	-0.1018	-0.1063	-0.0980	-0.0984
	Gold	-0.4191	-0.3879	-0.3681	-0.3654	-0.3668
Bond	Bitcoin	-0.0829	-0.1089	-0.0844	-0.0809	-0.0878
	Gold	0.2829	0.2996	0.2929	0.2914	0.2898
Gold	Bitcoin	-0.0113	-0.0138	-0.0147	-0.0140	-0.0107

Table 4: Standard deviations of dynamic correlations

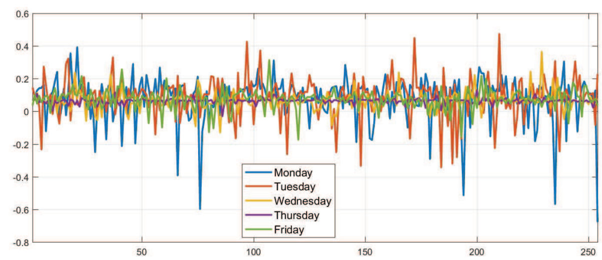
Asset 1	Asset 2	Monday	Tuesday	Wednesday	Thursday	Friday
S&P500	Bitcoin	0.1388	0.1201	0.0534	0.0162	0.0596
	Bond	0.1914	0.0820	0.0415	0.0414	0.0517
	Gold	0.2432	0.1142	0.0396	0.0214	0.0196
Bond	Bitcoin	0.0956	0.1923	0.0282	0.0140	0.0439
	Gold	0.1246	0.1298	0.0208	0.0283	0.0343
Gold	Bitcoin	0.0604	0.1205	0.0254	0.0281	0.0800

lations. Table 4 summarizes the standard deviations of the estimated dynamic correlations. As seen, the volatility of daily correlations between Bitcoin and traditional assets decreases over the week. This finding is also observed for stocks, for bonds and to a lesser extend for gold. Note that while cryptocurrency markets operate on the weekends, yet there is lower trading volume. Following Vega (2006), asset return and volatility are associated with a higher investors attention (and information flow in general). As a consequence, the increase in volatility at the beginning of the week may reflect higher information flow after a period of lower trading activity.

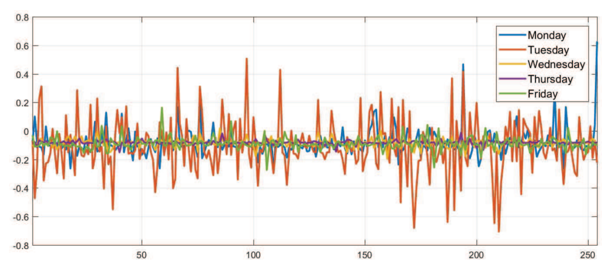
5 Conclusions

Examining correlations between Bitcoin and the traditional assets is a concern for academics and policy makers. Even though research on Bitcoin is fastly growing, the existing literature lacks a comprehensive, albeit flexible, framework to account for seasonality in returns, volatility and correlations between Bitcoin and traditional assets. Precisely, the current paper fills this gap.

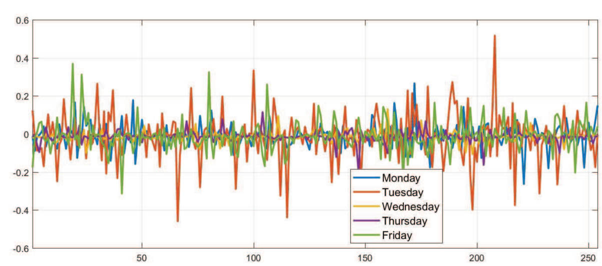
Based on the Periodic Generalized Dynamic Conditional Correlation methodology by Osborn et al. (2008), our results unveal additional evidence on the existence of the day-of-the-week effect on Bitcoin's returns and volatility. Specifically, Mondays are associated with higher returns, and Wednesdays with higher volatility. Moreover, we provide new evidence on the day-of-the-week effect in the correlation of Bitcoin with traditional assets, being higher at the beginning of the week. Another interesting result drawn from our empirical analysis is the



(a) Bitcoin-S&P500



(b) Bitcoin-Bond



(c) Bitcoin-Gold

Figure 2: Daily correlations between Bitcoin and traditional assets

decline in volatility of daily correlations over the week.

This result can offer further insights for portfolio managers about the timing and benefits of diversification, that can be adopted when measuring systematic risk, making decisions on asset asset allocation and hedging.

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