Do we Experience Day-of-the-week Effects in Returns and Volatility of Cryptocurrency?

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Abstract
This present paper investigates day-of-the-week effect in some notable cryptocurrency in terms of pricing and market capitalizations. We applied fractional integration regression approach with dummies. We found non-significance of day-of-the-week effect in returns, while there is possible evidence of Monday and Friday effects in volatility of Bitcoin only. Non-significance of day-of-the-week effect in returns of Bitcoin and some other cryptocurrencies further support market efficiency of these markets.

Key words: Bitcoin; Day-of-the-week Effect; Cryptocurrency; Market efficiency

1. Introduction

There are enormous literature investigating calendar effects such as the day-of-the-week effect, the Month of the Year effect, the January Effect, the Mid-year Effect, the Holiday Effect, the Halloween Effect, etc. These are all evidence against Efficient Market Hypothesis (EMH) market effect since in an efficient market, prices are expected to be unpredictable throughout the market period (Fama, 1970). As we know that the debate is still on the efficiency of cryptocurrency market, and possibility of such calendar effect negates our belief on the efficiency of cryptocurrency market. a more robust time based analysis is needed to thoroughly investigate such characteristic or inducement of market efficiency.

Empirical applications of cryptocurrency are growing in the literature. Meanwhile, the analyses involving calendar anomalies are still very few, particularly the day-of-the-week effect. Starting with the account of Kurihara and Fukushima (2017) who investigated day-of-the-week anomaly in Bitcoin returns using regression model with dummy variables and observed significant weekend effect, which is contrary to EMH belief. Decourt, Chohan and Perugini (2017) considered Bitcoin market only for possible day-of-the–week effect by using Student-t test for statistical significance of the average daily returns of Mondays compared to other day's returns and found that returns are significantly higher on Mondays. Caporale and Plastun (2018) considered various statistical methods such as average analysis, Student t-test, the analysis of variance (ANOVA), the kruskal Wallis and regression in investigating day-of-the-week effect in some cryptocurrency including the bitcoin. The authors found evidence of Monday effect in Bitcoin, while in other cryptocurrency, the day-of-the-week effect was not found. Durai and Paul (2018) asserted that weekly calendar anomaly found in Bitcoin is responsible for the argument on market efficiency level of Bitcoin since weekly effect could bias the estimate of market efficiency. Mbanga (2018) found evidence of high volatility clustering around Fridays than on Mondays in Bitcoin pricing. Similarly, Aharon and Qadan (2018) considered Bitcoin pricing between 2010 and 2017 and used the least squares and volatility modelling approaches and found evidences for weekly anomaly in both returns and volatility of Bitcoin.

This present paper investigates day-of-the-week effect in cryptocurrency using fractional integration framework in linear and nonlinear set up. Specifically, we apply parametric approach of Robinson (1994) based on Whittle function, that allows one to obtain three functional forms of no intercept, intercept only and constant and trend. For robustness in case of possible nonlinearity as a result of suspected structural breaks, we extend the analysis to include nonlinearity by using Chebyshev polynomial in time in the fractional integration framework.

2. Data and Statistical Method

We analyse time series of 13 popular and highly capitalized cryptocurrencies from Sunday 9 August 2015 to Saturday 5 January 2019. The datasets were sourced from the websites https://coinmetrics.io/data-downloads/. We obtained daily returns based on the transformation,

$$r_t = 100 * \log\left(close_t / open_t\right) \tag{1}$$

where r_t is the returns on tth day in percentage; $open_t$ is the open price on the tth day; $close_t$ is the open price on the tth day. We then obtained volatility proxy which is the squared log-returns (r_t^2).

For each of the time series, we consider fractional integration operation with dummy variables for the week days as follows:

$$(1-B)^d r_t = c_1 * D_{1,t} + c_2 * D_{2,t} + c_3 * D_{3,t} + c_4 * D_{4,t} + c_5 * D_{5,t} + c_6 * D_{6,t} + c_7 * D_{7,t} + \varepsilon_t \tag{2}$$

$$(1-B)^d r_t^2 = c_1 * D_{1,t} + c_2 * D_{2,t} + c_3 * D_{3,t} + c_4 * D_{4,t} + c_5 * D_{5,t} + c_6 * D_{6,t} + c_7 * D_{7,t} + \varepsilon_t \tag{3}$$

where B is the backward shift operator. The dummy variables $D_{i,t}\left(i = 1,...,7\right)$ are the weekly dummies of 1, 0 for week days, Sunday, Monday, …, Saturday with coefficients c_1, c_2, …, c_7. The random process, ε_t is the normal deviate, distributed normally with mean 0 and variance unity. The statistical significance of coefficients c_1, c_2, …, c_7 then provides information on the weekly anomaly of cryptocurrency returns and volatility. The fractional d value actually determines stationarity level of the time series, mathematically, $d = 0$ implies series stationarity, while d = 1 implies nonstationarity of the series, that is one unit difference is required to stabilize the series. Unit integration is too restrictive (see Granger and Joyeux, 1990; Hosking, 1991), d should be allowed to assume fractional values in both stationary/invertible range (-0.5<d<0.5) and non-stationary range (0.5<d<2). Values of d has different economic meaning which depends on level series, returns or volatility proxies under investigation. For example, non-significant of fractional *d* in log-returns series implies randomness of the series, that is non-prediction. This is the case of market efficiency since traders are not expected to have glimpse of future prediction based on returns history. Thus, market in-efficiency is when returns are predictable, and in this case, fractional d is expected to be significant. In the squared returns often used as proxy to volatility, values of d are expected to be significant in the range $0<d<0.5$. This is long memory range, since current observations rely closely on the past lagged observations.

In Table 1, we present the results for the case of returns with the assumption that fractional *d* value is unknown. We first observed significance of fractional *d* in the case of Doge, Ethereum, Maidsafecoin, Ripple, Stellar and Verge, implying market inefficiency of these cryptocurrencies, while Bitcoin and the remaining cryptocurrencies indicated market efficiency based on insignificance of fractional d values. By looking at the coefficients of weekly dummies, named “sun”, …, “sat”, these are not significant except in the case of Vertcoin which indicated significance on Thursday only.

Table 1: Day-of-the-week effect in Log-Returns with fractional *d* unknown

Cryptocurrency	*d*	Sun	Mon	Tue	Wed	Thu	Fri	Sat
Bitcoin	0.0246	0.0829	-0.0876	0.1069	-0.0259	-0.1152	0.0973	-0.0747
Dash	0.0012	0.1066	-0.0433	-0.3228	-0.0983	0.1922	0.0714	0.0946
Digibyte	0.0371	0.3188	-0.0575	-0.1974	0.0803	0.1281	-0.1305	-0.1379
Doge	**0.0628**	0.2981	-0.0466	-0.0781	-0.0441	-0.0415	-0.0585	-0.0881
Ethereum	**0.0700**	0.0048	0.1244	-0.2952	0.1716	-0.0201	0.1903	-0.1557
Litecoin	0.0253	0.2687	-0.0251	-0.0909	0.0407	-0.1941	-0.0836	0.0608
Maidsafecoin	**-0.0463**	-0.0386	0.1024	0.2387	-0.2143	0.1254	-0.1435	-0.0435
Monero	-0.0013	0.3109	0.1146	-0.0217	0.0105	-0.1178	-0.2825	-0.0122
Nem	-0.0223	-0.1238	0.0270	0.4425	-0.1863	-0.2007	-0.0873	0.1602
Ripple	**0.0561**	-0.3000	0.1943	-0.4159	-0.0893	-0.0516	0.2865	0.3721
Stellar	**0.0619**	0.1176	0.0991	0.0679	0.0006	-0.1653	-0.1940	0.0195
Verge	**-0.0939**	0.7343	0.3252	-1.1561	0.5935	-0.4702	0.1105	0.2438
Vertcoin	-0.0354	0.3315	0.2309	-0.5000	-0.3005	**0.6255**	-0.1503	-0.1938

In bold, significant parameters at 5% level.

By looking at the possibility of day-of-the-week effect in the volatility. The results are presented in Table 2. We observe different persistence of volatility as indicated in the fractional *d* value. Here, we see that the volatility in Stellar persists more than other cryptocurrency, while Digibyte has lowest persistence of volatility. Meanwhile, day-of-the-week effect volatility is not significant throughout.

By assuming that fractional d is known to be 0 in both return and volatility proxy, we present results in Table 3 and 4. In Table 3, we found non-significance of day-of-the-week effect in returns throughout, implying that virtual trading of cryptocurrency is not dependent on a particular day.

Table 2: Day-of-the-week effect in Squared Returns with unknown *d*

Cryptocurrency	d	Sun	Mon	Tue	Wed	Thu	Fri	Sat
Bitcoin	**0.1675**	-0.5453	-1.5042	-0.0310	0.1970	-0.0293	1.2845	-0.0906
Dash	**0.1237**	0.2641	-0.3005	0.5262	-1.0977	1.3741	1.4764	-2.2431
Digibyte	**0.0694**	2.9670	-7.6595	-1.6508	10.5074	3.0260	-4.6547	-2.5354
Doge	**0.1726**	0.5958	0.8230	-1.3001	1.8535	-1.4533	-0.2031	-0.3160
Ethereum	**0.1891**	-0.3649	-1.7774	2.1517	4.4136	0.8115	4.1352	0.5406
Litecoin	**0.1301**	-1.3733	-3.5370	-0.3649	0.1534	0.9872	3.3280	0.8064
Maidsafecoin	**0.1088**	-2.3097	-1.9429	0.5770	1.6237	2.9096	-0.3973	-0.4607
Monero	**0.1187**	-1.0577	-0.4135	2.5724	1.4421	-0.5443	0.1002	-2.0994
Nem	**0.1214**	-5.4804	-3.1722	1.1403	-1.8326	-1.0437	2.5568	7.8318
Ripple	**0.2284**	-7.0637	4.1568	0.6657	-0.6515	-3.5652	6.3413	0.1166
Stellar	**0.3130**	-0.9259	0.2098	1.5282	1.7505	-1.1786	-0.3424	-1.0417
Verge	**0.2614**	7.5572	-3.0009	-17.4911	-1.0656	10.9316	0.4776	2.5911
Vertcoin	**0.4183**	-5.4532	-0.1381	-4.5289	0.3203	6.6231	4.5659	-1.3889

In bold, significant parameters at 5% level.

Table 3: Day-of-the-week effect in Log-Returns with *d* = 0

Cryptocurrency	Sun	Mon	Tue	Wed	Thu	Fri	Sat
Bitcoin	0.0847	-0.0811	0.1086	-0.0242	-0.1135	0.0990	-0.0730
Dash	0.1066	-0.0432	-0.3228	-0.0983	0.1922	0.0714	0.0946
Digibyte	0.3215	-0.0725	-0.1954	0.0824	0.1301	-0.1285	-0.1357
Doge	0.3065	-0.0330	-0.0700	-0.0364	-0.0339	-0.0509	-0.0805
Ethereum	-0.0001	0.1230	-0.2974	0.1693	-0.0227	0.1872	-0.1593
Litecoin	0.2718	-0.0185	-0.0878	0.0438	-0.1911	-0.0805	0.0639
Maidsafecoin	-0.0425	0.0979	0.2350	-0.2180	0.1217	-0.1472	-0.0471
Monero	0.3109	0.1147	-0.0217	0.0105	-0.1178	-0.2826	-0.0122

Nem	-0.1271	0.0117	0.4398	-0.1890	-0.2035	-0.0901	0.1574
Ripple	-0.2994	0.1950	-0.4157	-0.0891	-0.0514	0.2867	0.3722
Stellar	0.1270	0.0994	0.0765	0.0097	-0.1560	-0.1847	0.0288
Verge	0.7153	0.3031	-1.1738	-0.6112	0.4525	0.0926	0.2257
Vertcoin	0.3262	0.2212	-0.5051	-0.3058	0.6202	-0.1557	-0.1992

In bold, significant parameters at 5% level.

The case of volatility in cryptocurrency is presented in Table 4. We only observe significance in the case of Bitcoin only where Monday and Friday are significant. This result agrees with Mbanga (2018).

Table 4: Day-of-the-week effect in Squared Returns with *d* = 0

Cryptocurrency	Sun	Mon	Tue	Wed	Thu	Fri	Sat
Bitcoin	-0.4518	**-1.4010**	0.0723	0.3014	0.0754	**1.3890**	0.0146
Dash	0.2641	-0.3005	0.5263	-1.0977	1.3742	1.4765	-2.2430
Digibyte	2.9670	-7.6595	-1.6508	10.5074	3.0260	-4.6547	-2.5354
Doge	0.5958	0.8230	-1.3000	1.8535	-1.4532	-0.2030	-0.3160
Ethereum	-1.7907	-3.1687	0.7556	3.0098	-0.6066	2.7043	-0.9036
Litecoin	-1.3733	-3.5370	-0.3649	0.1534	0.9873	3.3281	0.8064
Maidsafecoin	-2.3097	-1.9428	0.5770	1.6238	2.9097	-0.3973	-0.4607
Monero	-1.0577	-0.4134	2.5724	1.4421	-0.5443	0.1002	-2.0994
Nem	-5.4803	-3.1722	1.1403	-1.8326	-1.0437	2.5568	7.8318
Ripple	-7.0637	4.1568	0.6657	-0.6515	-3.5652	6.3413	0.1166
Stellar	-0.9259	0.2098	1.5282	1.7506	-1.1786	-0.3424	-1.0417
Verge	7.5572	-3.0009	-17.4911	-1.0656	10.9316	0.4776	2.5912
Vertcoin	-5.4532	-0.1381	-4.5289	0.3203	6.6231	4.5659	-1.3889

In bold, significant parameters at 5% level.

3. Concluding remarks

Trading at cryptocurrency markets is 24 hours a day and 7 days a week (24/7). The present paper investigated the possibility of days-of-the-week effect in both return and volatility of 13 sampled cryptocurrencies from Sunday 9 August 2015 to Saturday 5 January 2019. Our methodological approach is different from other works, since we apply dummy variable regression approach with fractional integration operation. By assuming fractional integration d to be unkown in the test regression, we found no evidence of day-of-the-week effect in both returns and volatility of those cryptocurrencies. Also, fractional d are only significant in Doge, Ethereum, Maidsafecoin, Ripple, Stellar and Verge implying market inefficiency of these markets. Thus, Bitcoin market is perfectly efficient based on our results. While by assuming that fractional d is 0, we found no evidence of day-of-the-week effect since those dummy coefficients are not significant throughout. In this case, volatility in Bitcoin market has day-of-the-week effect as Monday and Friday dummies are only significant.

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