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Is there Day-of-the-week Effects in Returns and Volatility of Cryptocurrency?

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Abstract

This present paper investigates day-of-the-week effects in some notable cryptocurrency in terms of pricing and market capitalizations. Fractional integration regression approach with dummies method is applied. The results show non-significance of day-of-the-week effects in returns, while there is possible evidence of Monday and Friday effects in the volatility of Bitcoin only. Non-significance of day-of-the-week effects 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

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 evidences against Efficient Market Hypothesis (EMH) since in an efficient market, prices are expected to be unpredictable throughout the market period [1].The discussion is still in its infancy stage on the efficiency of cryptocurrency market, and the possibility of such calendar effect negates the belief on the efficiency of cryptocurrency market. A more robust time-based analysis is needed to thoroughly investigate such characteristic as well as the market efficiency stage of the currency.

Currently, there are quite many literature on empirical applications of cryptocurrency, 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 [2], who investigated the 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 [3] 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 [4] considered various statistical methods, such as average analysis, Student t-test, the Analysis of Variance (ANOVA), the Kruskal Wallis test and regression methods in investigating the day-of-the-week effect in some cryptocurrency including the Bitcoin. The authors found evidence of Monday effect in Bitcoin, while in other cryptocurrencies, the day-of-the-week effect was not found. Durai and Paul [5] 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 [6] found evidence of higher volatility clustering around Fridays than on Mondays in Bitcoin pricing. Similarly, Aharon and Qadan [7] considered Bitcoin pricing between 2010 and 2017 using the least squares and volatility modelling approaches, they found evidences for weekly anomaly in both returns and volatility of Bitcoin. Ma and Tanizaki [8] investigated day-of-the-week effect in Bitcoin returns and volatility using Bitcoin prices from January 2013 to December 2018. For the day-of-the-week investigation in returns, the regression model was used, while in the volatility, the time-varying Stochastic Volatility model was used. The results obtained showed that the day-of-the-week effect varied with sample size, while higher and more significant volatilities were found on Monday and Thursday.

This present paper investigates the day-of-the-week effect in cryptocurrencies using fractional integration framework in linear and nonlinear set up. Specifically, the parametric approach of Robinson [9] based on Whittle function is applied. This approach allows one to obtain three functional forms of no intercept, intercept only and constant and time trend. For robustness in the case of possible nonlinearity as a result of suspected structural breaks, the analysis is extended to include nonlinearity by using Chebyshev polynomial in time in the fractional integration framework.

Data and Statistical Method

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

$$r_t = 100 * \log\left(close_t / open_t\right) \quad (1)$$

where r_t is the returns on t^{th} day in percentage; $open_t$ is the open price on the t^{th} day; $close_t$ is the closing price on the t^{th} day. Volatility proxy, which is the squared log-returns (r_t^2) is then obtained.

For each of the series, fractional integration operation with dummy variables is considered for the week days as follows:

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

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

where B is the backward shift operator. The dummy variables $D_{i,t}$ (i = 1,…,7) are the weekly dummies of 1, 0 for week days, Sunday, Monday, …, Saturday with coefficients $c_1, c_2, \ldots, c_7$. The random process, e_t is the normal deviate, distributed normally with mean 0 and variance unity. The statistical significance of coefficients $c_1, c_2, \ldots, c_7$ then provides information on the weekly anomaly of cryptocurrency returns and volatility.

The fractional d value actually determines the level of the stationarity of the time series. Mathematically, d = 0 implies the series is stationary, while d = 1 implies nonstationarity of the series, that is,a unit difference is required to attain stationarity of the series. Unit integration is too restrictive (see [10, 11]),hence 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 the level series, returns or volatility proxies under investigation. For example, the non-significance of fractional d in log-returns series implies randomness in the series, that is, the non-prediction of the series. 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 referred to as long memory range, since current observations rely on the past lagged observations that are very close.

In Table 1, the results for the case of returns with the assumption that fractional d value is unknown is presented. First, the significance of fractional d in the case of Doge, Ethereum, Maidsafecoin, Ripple, Stellar and Verge was observed, 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 Thursdays 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 the day-of-the-week effect in the volatility, with the results presented in Table 2, different persistence of volatility as indicated in the fractional d value are observed. Here, the volatility in Stellar persists more than other cryptocurrency, while Digibyte has lowest persistence of volatility. Meanwhile, the day-of-the-week effect volatility is not significant throughout.

By assuming that fractional d is known to be 0 in both returns and volatility proxies, the results are presented in Table 3 and 4. In Table 3, non-significance of the day-of-the-week effect is found 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 and the results only showed evidence of significant Monday and Friday effects in the case of Bitcoin only. This result agrees with Mbanga [6].

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.

Conclusion

Trading at cryptocurrency markets is 24 hours a day and 7 days a week (24/7). This paper investigates the possibility of the day-of-the-week effect in both returns and volatility of 13 notable cryptocurrencies, with daily prices from Sunday 9 August 2015 to Saturday 5 January 2019. Dummy variable regression approach with fractional integration operation which is different from the approach used by other authors is applied. By assuming the fractional integration *d* to be unknown in the test regression, it is established that there is no evidence of the day-of-the-week effect in both returns and volatility of the 13 cryptocurrencies. Also, fractional differences *d* are only significant in Doge, Ethereum, Maidsafecoin, Ripple, Stellar and Verge implying market inefficiency of these markets. Thus, Bitcoin market is dubbed efficient based on the observed results. While by assuming that fractional difference *d* is 0, the results showed no evidence of the day-of-the-week effect, since those dummy coefficients are not significant. The results further indicate significance of Monday and Friday dummies in the squared returns of Bitcoin prices implying evidence of the day-of-the-week effect only in the volatility of Bitcoin.

References

[1] Fama, E.F. 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25(2), 383–417.

[2] Kurihara, Y., Fukushima, A., 2017. The market efficiency of Bitcoin: a weekly anomaly. Perspect. *Journal of Applied Finance and Banking*, 7 (3), 57–64.

[3] Decourt, R.F., Chohan, U.W. and Perugini, M.L. 2017. Bitcoin Returns and the Monday Effect. *Horizontes Empresariales*, 16, 4-14.

[4] Caporale, G.M. and Plastun, A. 2018. The day of the week effect in the cryptocurrency market. Finance Research Letters, https://doi.org/10.1016/j.frl.2018.11.012

[5] Durai, S.R.S. and Paul, S. 2018. Calendar anomaly and the degree of market inefficiency of Bitcoin. *Madras School of Economics working paper* No. 168/2018.

[6] Mbaga, C.L. 2018. The day-of-the-week pattern of price clustering in bitcoin. *Applied Economics Letters*, https://doi.org/10.1080/13504851.2018.1497844

[7] Aharon, D.Y. and Qadan, M. 2018. Bitcoin and the day-of-the-week effect. *Finance Research Letters*, https://doi.org/10.1016/j.frl.2018. 12. 004

[8] Ma, D. and Tanizaki, H. (2019). The day-of-the-week effect on Bitcoin return and volatility. Research in International Business and Finance, https://doi.org/doi:10.1016/j.ribaf.2019.02.003

[9] Robinson, P.M. 1994. Efficient tests of nonstationary hypotheses. *Journal of the American Statistical Association*, 89, 1420-1437.

[10] Granger, C.W.J. and Joyeux, R. 1980. An introduction to long memory time series and fractionally differencing. *Journal of Time Series Analysis*, 1, 15-29.

[11] Hosking, J.R.M. 1981. Fractional differencing. *Biometrika*, 68, 165-176.

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