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# The Day of the Week Effect in the Crypto Currency Market

## Abstract

This paper examines the day of the week effect in the crypto currency market using a variety of statistical techniques (average analysis, Student's t-test, ANOVA, the Kruskal-Wallis test, and regression analysis with dummy variables) as well as a trading simulation approach. Most crypto currencies (LiteCoin, Ripple, Dash) are found not to exhibit this anomaly. The only exception is BitCoin, for which returns on Mondays are significantly higher than those on the other days of the week. In this case the trading simulation analysis shows that there exist exploitable profit opportunities that can be interpreted as evidence against efficiency of the crypto currency market.

JEL-Codes: G120, C630.

Keywords: efficient market hypothesis, day of the week effect, crypto currency, BitCoin, anomaly, trading strategy.

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## 1. Introduction

There exists a vast literature analysing calendar anomalies (the Day of the Week Effect, the Turn of the Month Effect, the Month of the Year Effect, the January Effect, the Holiday Effect, the Halloween Effect etc.), and whether or not these can be seen as evidence against the Efficient Market Hypothesis (EMH – see, e.g., Fama, 1965; Samuelson, 1965; Jensen, 1978). However, with one exception (Kurihara and Fukushima, 2017) to date no study has analysed such issues in the context of the crypto currency market – this being a newly developed market, it might still be relatively inefficient and it might offer more opportunities for making abnormal profits by adopting trading strategies exploiting calendar anomalies. We focus in particular on the day of the week effect, and for robustness purposes apply a variety of statistical methods (average analysis, Student's t-test, ANOVA, the Kruskal-Wallis test, and regression analysis with dummy variables) as well as a trading robot approach that replicates the actions of traders to examine whether or not such an anomaly gives rise to exploitable profit opportunities.

The paper is structured as follows: Section 2 briefly reviews the literature on the day of the week effect; Section 3 outlines the empirical methodology; Section 4 presents the empirical results; Section 5 offers some concluding remarks.

## 2. Literature Review

The day of the week effect (concerning statistically significant differences between returns on different days of the week) was one of the first calendar anomalies to be examined. Fields (1931) showed that the best trading day of the week is Saturday. Cross (1973) provided evidence of statistical differences in Friday-Monday data in the US stock market. French (1980) reported negative returns on Mondays. Further studies found evidence of a positive Friday/negative Monday pattern (see Gibbons and Hess, 1981; Rogalski, 1984; Smirlock and Starks, 1986, etc.). Other studies on the stock market include Sias and Starks

(1995), Hsaio and Solt (2004), and Caporale et al. (2016), whilst commodity markets were analysed by Singal and Tayal (2014), and the FOREX by Caporale et al. (2017). Ariel (1990), Fortune (1998) and Schwert (2003) all reported evidence against the Monday effect in developed markets, but this anomaly still appears to exist in many emerging markets (Caporale and Plastun, 2017).

The crypto currency market is rather young but sufficient data are now available to examine its properties. Dwyer (2014), Cheung et al. (2013) and Carrick (2016) show that it is much more volatile than other markets. Brown (2014) provides evidence of short-term price predictability of the BitCoin. The inefficiency of the BitCoin market is also documented by Urquhart (2016), whilst Bartos (2015) reports that this market immediately reacts to the arrival of new information and can therefore be characterised as efficient. Halaburda and Gandal (2014) analyse correlations in daily closing prices.

However, so far the only study examining anomalies in this market is due to Kurihara and Fukushima (2017), who focus exclusively on the BitCoin, which is not necessarily representative of the crypto currency market as a whole. The present paper aims to fill this gap in the literature by providing much more extensive evidence on the day of the week effect in this market.

## 3. Data and Methodology

We examine daily data for 4 crypto currencies, choosing those with the highest market capitalisation and the longest data span (2013-2017), namely BitCoin, LiteCoin, Ripple and Dash. The data source is CoinMarketCap (https://coinmarketcap.com/coins/). More information on the crypto currency market is provided in Table 1 below.

**Table 1: Capitalisation of the crypto currency market (25.09.2017)**

| # | Name | Market Cap | Price | Circulating Supply | Data starts from |
|---|---|---|---|---|---|
| 1 | Bitcoin | $61,661,715,957 | $3717.96 | 16,584,825 BTC | 28 apr 2013 |
| 2 | Ethereum | $27,047,930,739 | $285.32 | 94,798,247 ETH | 07 aug 2015 |
| 3 | Bitcoin Cash | $7,048,650,600 | $424.34 | 16,611,013 BCH | 23 jul 2017 |
| 4 | Ripple | $6,743,378,097 | $0.175866 | 38,343,841,883 XRP * | 04 aug 2013 |
| 5 | Dash | $2,662,327,218 | $351.38 | 7,576,753 DASH | 14 feb 2014 |
| 6 | Litecoin | $2,546,042,771 | $47.97 | 53,077,832 LTC | 28 apr 2013 |
| 7 | NEM | $1,978,722,000 | $0.219858 | 8,999,999,999 XEM * | 01 apr 2015 |
| 8 | IOTA | $1,449,700,153 | $0.521563 | 2,779,530,283 MIOTA * | 13 jun 2017 |
| 9 | Monero | $1,360,521,393 | $89.94 | 15,127,056 XMR | 21 may 2014 |
| 10 | Ethereum Classic | $1,004,178,222 | $10.48 | 95,822,190 ETC | 24 jun 2016 |

*Cryptocurrency Market Capitalizations. Source: https://coinmarketcap.com/coins/

Returns are computed as follows:

$$R_i = \left(\frac{Close_i}{Close_{i-1}} - 1\right) \times 100\% \,, \qquad (1)$$

where $R_i$ – returns on the *i-th* day in %;

$Open_i$ – open price on the *i-th* day;

$Close_i$ – close price on the *i-th* day.

Average analysis provides preliminary evidence on whether there are differences between returns for the different days of the week. Both parametric and non-parametric tests are carried out given the evidence of fat tails and kurtosis in returns. The Null Hypothesis (H0) in each case is that the data belong to the same population, a rejection of the null suggesting the presence of an anomaly.

We carry out Student's t, ANOVA and Kruskal-Wallis tests for the whole sample, and also for sub-samples in order to make comparisons between periods that might be characterised by an anomaly and the others. In addition we run multiple regressions including a dummy variable to identify the day of the week effect:

$$\mathrm{Y_t} = \mathrm{a_0} + \mathrm{a_1 D_{1t}} + \mathrm{a_2 D_{2t}} + \cdots + \mathrm{b_n D n_t} + \varepsilon_\mathrm{t} \qquad (2)$$

where $Y_t$ – return in period *t;*

$\mathrm{a_n}$– mean return on the n day of the week

$\mathrm{D_{nt}}$– a dummy variable for the n day of the week, equal to 1 for observations corresponding to that day and to 0 otherwise

$\varepsilon_\mathrm{t}$ – error term for period *t*.

The size, sign and statistical significance of the dummy coefficients provide information about possible anomalies.

If an anomaly is detected we then apply a trading robot approach that simulates the actions of a trader according to an algorithm (trading strategy) with the aim of establishing whether or not that anomaly gives rise to exploitable profit opportunities, which could be seen as evidence against market efficiency. This is a programme in the MetaTrader terminal that has been developed in MetaQuotes Language 4 (MQL4) and used for the automation of analytical and trading processes. Trading robots (called experts in MetaTrader) allow to analyse price data and manage trading activities on the basis of the signals received.

If a strategy results in the number of profitable trades > 50% and/or total profits from trading are > 0, then we conclude that there is a market anomaly. The results are presented in the "Report" in Appendix A. The most important indicators given in the "Report" are:

- Total net profit — financial result of all trades. This parameter represents the difference between "Gross profit" and "Gross loss";

- Expected payoff — mathematical expectation of a win. This parameter represents the average profit/loss for one trade. It also shows the expected profitability/unprofitability of the next trade;
- Total trades — total number of trade positions;
- Bars in test – the number of observations used for testing.

The findings are summarised in the “Graph” section of the “Report”: this represents the account balance and general account status considering open positions. The “Report” also provides full information about all the simulated transactions and their financial results.

To make sure that the results we obtain are statistically different from the random trading ones we carry out t-tests. We chose this approach instead of carrying out z-tests because the sample size is less than 100. A t-test compares the means from two samples to see whether they come from the same population. In our case the first is the average profit/loss factor of one trade applying the trading strategy, and the second is equal to zero because random trading (without transaction costs) should generate zero profit.

The null hypothesis (H0) is that the mean is the same in both samples, and the alternative (H1) that it is not. The computed values of the t-test are compared with the critical one at the 5% significance level. Failure to reject H0 implies that there are no advantages from exploiting the trading strategy being considered, whilst a rejection suggests that the adopted strategy can generate abnormal profits.

An example of the t-test is presented in Table 2.

**Table 2: Example of the t-test for the trading strategy effectiveness evaluation: BitCoin testing in 2016**

| Parameter | Value |
|---|---|
| Number of the trades | 51 |
| Total profit | 837 |

| | |
|---|---|
| Average profit per trade | 59 |
| Standard deviation | 16 |
| t-test | 107 |
| t critical (0,95) | 1,23 |
| Null hypothesis | 1,78 |

As can be seen there is no evidence of statistically significant difference in terms of total net profits relative to the random trading case, and therefore no market inefficiency is detected.

## 4. Empirical Results

The complete set of results can be found in Appendix B. The average analysis (Figures B.1, B.2, B.3 and B.4) provides preliminary evidence of a day of the week anomaly in the dynamics of BitCoin and LiteCoin, whilst in the cases of Ripple and Dash it is unclear whether or not this is present. The results of the parametric and non-parametric tests are reported in Appendices C, D, E and F) and summarised in Table 3.

**Table 3: Overview of the results for the Crypto currency market**

| Crypto currency/Methodology | Average analysis | Student's t-test | ANOVA | Kruskal - Wallis test | Regression analysis with dummies |
|---|---|---|---|---|---|
| BitCoin | + | + | + | + | + |
| LiteCoin | + | - | - | - | - |
| Ripple | - | - | - | - | - |
| Dash | - | - | - | + | - |

There is clear evidence of an anomaly only in the case of BitCoin. The next step is to apply a trading simulation approach. First we design appropriate trading rules for the days when long or short positions respectively should be opened (see Table 4 for details).

**Table 4: Anomalies by day for the BitCoin**

| Day of the week | Average analysis | t-test | ANOVA | Kruskal - Wallis test | Regression analysis | Overall |
|---|---|---|---|---|---|---|
| Monday | + | + | + | + | + | 5 |
| Tuesday | - | - | - | - | - | 0 |
| Wednesday | + | - | - | - | + | 2 |
| Thursday | - | - | - | - | - | 0 |
| Friday | - | - | - | - | + | 1 |

Since the anomaly occurs on Mondays (when returns are much higher than on the other days of the week) the trading strategy will be the following: open long positions on Monday and close them at the end of this day. The trading simulation results are reported in Table 5.

**Table 5 – Summary of the trading simulation results**

| Parameter | Full sample | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|---|
| Profit trades (% of total) | 60 | 75 | 39 | 60 | 59 | 71 |
| Number of the trades | 245 | 52 | 52 | 52 | 51 | 38 |
| Total profit | 16990 | 3730 | -315 | 1076 | 837 | 11662 |
| Average profit per trade | 69 | 72 | -6 | 21 | 16 | 307 |
| Standard deviation | 555 | 341 | 228 | 84 | 107 | 1288 |
| t-test | 2.01 | 1.56 | -0.13 | 1.96 | 1.23 | 1.48 |
| t critical (0,95) | 1.78 | 1.78 | 1.78 | 1.78 | 1.78 | 1.78 |
| Null hypothesis | rejected | confirmed | confirmed | rejected | confirmed | confirmed |

In general this strategy is profitable, both for the full sample and for individual years, but in most cases the results are not statistically different from the random trading case, and therefore they do not represent evidence of market inefficiency.

## 5. Conclusions

This paper examines the day of the week effect in the crypto currency market focusing on BitCoin, LiteCoin, Ripple and Dash. Applying both parametric and non-parametric methods we find evidence of an anomaly (abnormal positive returns on Mondays) only in the case of BitCoin. Further, using a trading simulation approach we show that a trading strategy based on this anomaly is profitable for the whole sample (2013-2017): it generates net profit with probability 60% and these results significantly differ from the random ones. However, in the case of individual years the opposite conclusions are reached. There is no evidence that the crypto currency market as a whole is inefficient.

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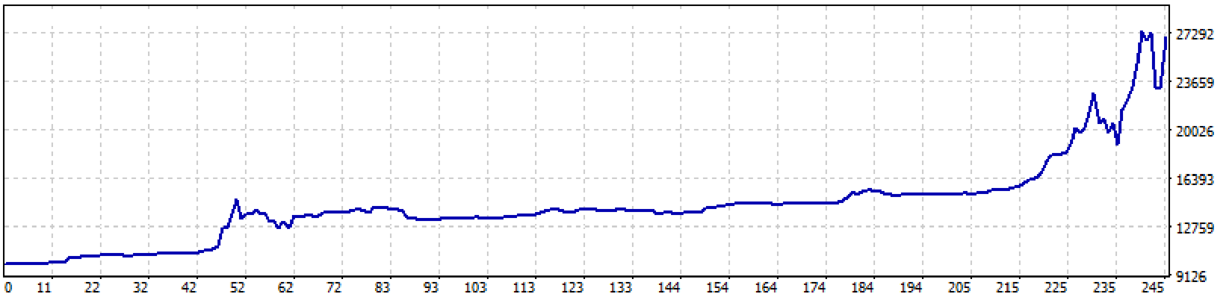
## Appendix A

### Table A1 – Example of trading strategy testing report

| | | | | | |
|---|---|---|---|---|---|
| Symbol | | BTCUSD (1 Lot= 10 BTC) | | | |
| Period | | Daily (D1) 2013.01.01 00:00 - 2017.09.22 00:00 (2013.01.01 - 2017.12.31) | | | |
| Parameters | | Lots=1; | | | |
| Bars in test | 2423 | Ticks modelled | 63927 | Modelling quality | n/a |
| Mismatched charts errors | 0 | | | | |
| Initial deposit | 10000 | | | Spread | 2 |
| Total net profit | 16990 | Gross profit | 35137.7 | Gross loss | -18147.7 |
| Profit factor | 1.94 | Expected payoff | 69.35 | | |
| Absolute drawdown | 849.6 | Maximal drawdown | 6322.60 (22.68%) | Relative drawdown | 39.54% (5983.00) |
| | | | | | |
| Total trades | 245 | Short positions (won %) | 0 (0.00%) | Long positions (won %) | 245 (60.00%) |
| | | Profit trades (% of total) | 147 (60.00%) | Loss trades (% of total) | 98 (40.00%) |
| Largest | | profit trade | 3811.8 | loss trade | -4079.2 |
| Average | | profit trade | 239.03 | loss trade | -185.18 |
| Maximum | | consecutive wins (profit in money) | 9 (475.80) | consecutive losses (loss in money) | 6 (-803.50) |
| Maximal | | consecutive profit (count of wins) | 8541.80 (5) | consecutive loss (count of losses) | -4165.80 (2) |
| Average | | consecutive wins | 2 | consecutive losses | 2 |

### Graph A1 – Graph of balance dynamics



## Table A2 – Statement (a Section)

| # | Time | Type | Order | Size | Price | S / L | T / P | Profit | Balance |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 07.01.2013 0:00 | buy | 1 | 1 | 13.47 | 0 | 0 | | |
| 2 | 07.01.2013 23:59 | close | 1 | 1 | 13.59 | 0 | 0 | 1.2 | 10001.2 |
| 3 | 14.01.2013 0:00 | buy | 2 | 1 | 14.21 | 0 | 0 | | |
| 4 | 14.01.2013 23:59 | close | 2 | 1 | 14.3 | 0 | 0 | 0.9 | 10002.1 |
| 5 | 21.01.2013 0:00 | buy | 3 | 1 | 15.72 | 0 | 0 | | |
| 6 | 21.01.2013 23:59 | close | 3 | 1 | 16.8 | 0 | 0 | 10.8 | 10012.9 |
| 7 | 28.01.2013 0:00 | buy | 4 | 1 | 17.84 | 0 | 0 | | |
| 8 | 28.01.2013 23:59 | close | 4 | 1 | 18.72 | 0 | 0 | 8.8 | 10021.7 |
| 9 | 04.02.2013 0:00 | buy | 5 | 1 | 20.62 | 0 | 0 | | |
| 10 | 04.02.2013 23:59 | close | 5 | 1 | 20.43 | 0 | 0 | -1.9 | 10019.8 |
| 11 | 11.02.2013 0:00 | buy | 6 | 1 | 23.99 | 0 | 0 | | |
| 12 | 11.02.2013 23:59 | close | 6 | 1 | 24.65 | 0 | 0 | 6.6 | 10026.4 |
| 13 | 18.02.2013 0:00 | buy | 7 | 1 | 26.92 | 0 | 0 | | |
| 14 | 18.02.2013 23:59 | close | 7 | 1 | 26.95 | 0 | 0 | 0.3 | 10026.7 |
| 15 | 25.02.2013 0:00 | buy | 8 | 1 | 29.91 | 0 | 0 | | |
| 16 | 25.02.2013 23:59 | close | 8 | 1 | 30.4 | 0 | 0 | 4.9 | 10031.6 |
| 17 | 04.03.2013 0:00 | buy | 9 | 1 | 34.52 | 0 | 0 | | |
| 18 | 04.03.2013 23:59 | close | 9 | 1 | 36.15 | 0 | 0 | 16.3 | 10047.9 |
| 19 | 11.03.2013 0:00 | buy | 10 | 1 | 46.02 | 0 | 0 | | |
| 20 | 11.03.2013 23:59 | close | 10 | 1 | 48.4 | 0 | 0 | 23.8 | 10071.7 |
| 21 | 18.03.2013 0:00 | buy | 11 | 1 | 47.42 | 0 | 0 | | |
| 22 | 18.03.2013 23:59 | close | 11 | 1 | 51.6 | 0 | 0 | 41.8 | 10113.5 |
| 23 | 25.03.2013 0:00 | buy | 12 | 1 | 71.52 | 0 | 0 | | |
| 24 | 25.03.2013 23:59 | close | 12 | 1 | 73.6 | 0 | 0 | 20.8 | 10134.3 |
| 25 | 01.04.2013 0:00 | buy | 13 | 1 | 93.05 | 0 | 0 | | |
| 26 | 01.04.2013 23:59 | close | 13 | 1 | 104 | 0 | 0 | 109.5 | 10243.8 |
| 27 | 08.04.2013 0:00 | buy | 14 | 1 | 162.32 | 0 | 0 | | |
| 28 | 08.04.2013 23:59 | close | 14 | 1 | 187.5 | 0 | 0 | 251.8 | 10495.6 |
| 29 | 15.04.2013 0:00 | buy | 15 | 1 | 90.02 | 0 | 0 | | |
| 30 | 15.04.2013 23:59 | close | 15 | 1 | 82.39 | 0 | 0 | -76.3 | 10419.3 |
| 31 | 22.04.2013 0:00 | buy | 16 | 1 | 118.52 | 0 | 0 | | |
| 32 | 22.04.2013 23:59 | close | 16 | 1 | 127.4 | 0 | 0 | 88.8 | 10508.1 |
| 33 | 29.04.2013 0:00 | buy | 17 | 1 | 134.42 | 0 | 0 | | |
| 34 | 29.04.2013 23:59 | close | 17 | 1 | 144 | 0 | 0 | 95.8 | 10603.9 |

## Appendix B

## Empirical results for the Day of the Week Effect

### Average analysis

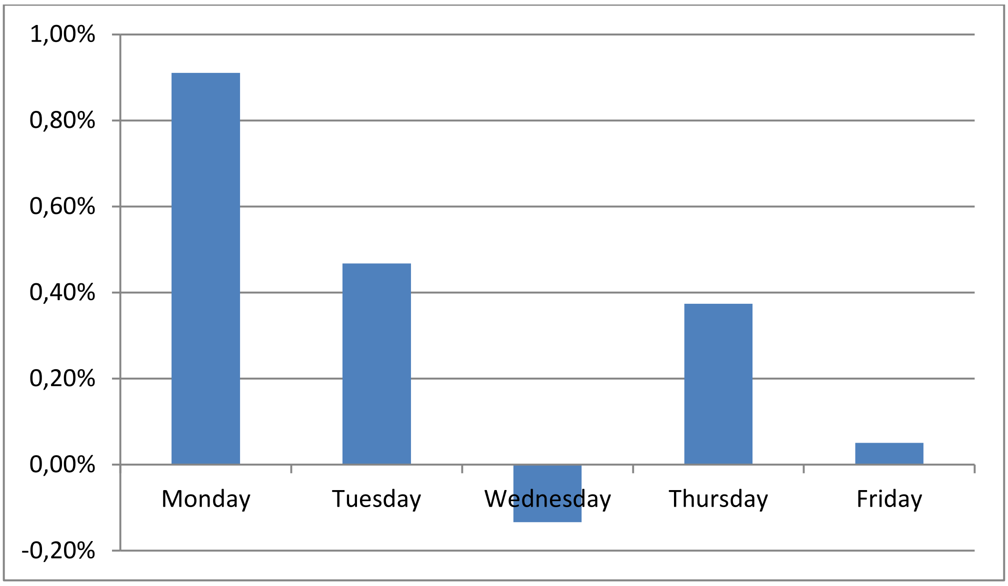



Figure B.1 – BitCoin

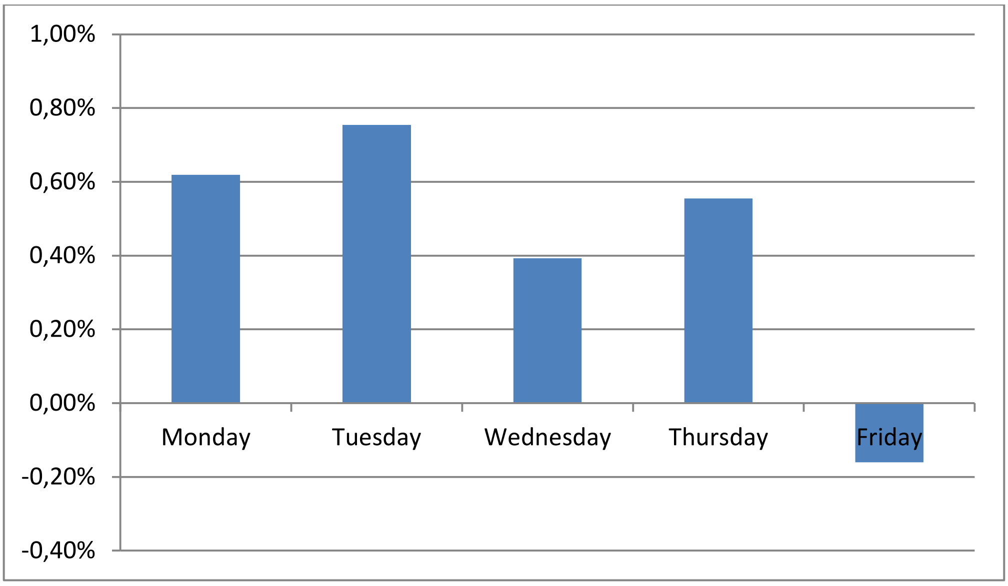



Figure B.2 – LiteCoin

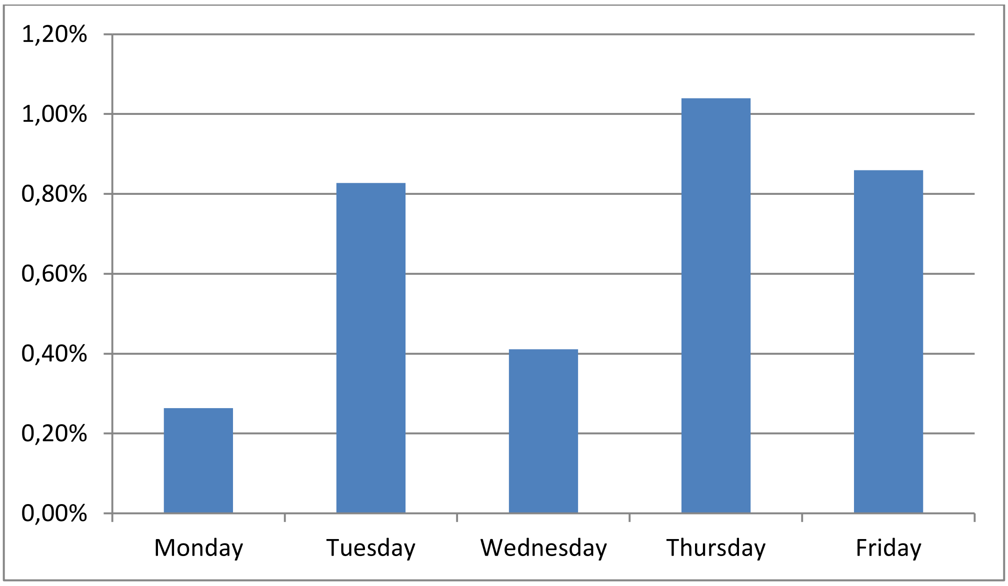



Figure B.3 – Ripple

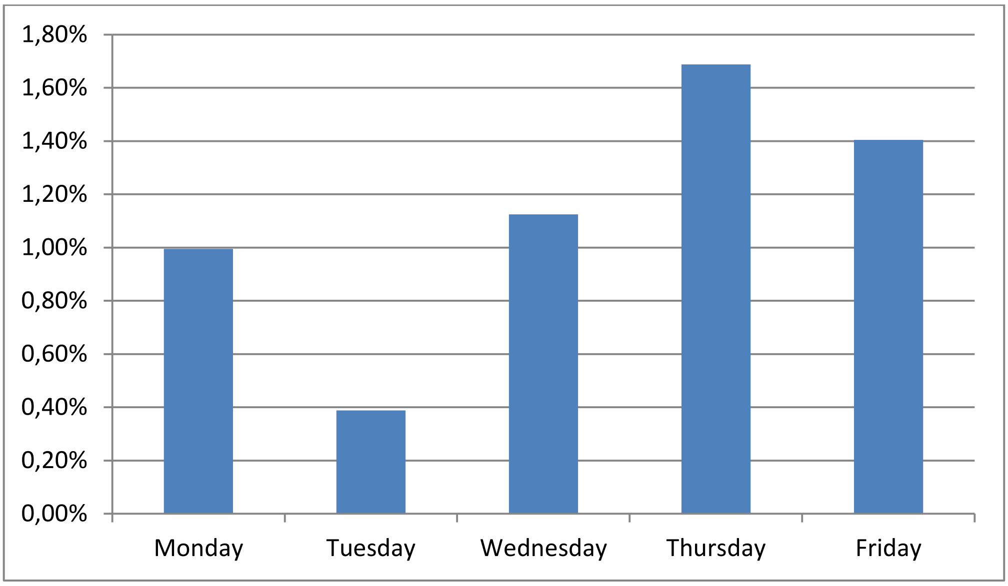



Figure B.4 – Dash

## Appendix C

## Parametric tests: Student's t-test

**Table C.1: T-test of the Day of the Week Effect for BitCoin**

| Parameter | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| Population 1 (data without day of analysis) | | | | | |
| Mean,% | 0.91% | 0.47% | -0.13% | 0.37% | 0.05% |
| Standard deviation,% | 4.82% | 4.05% | 4.58% | 5.05% | 4.20% |
| Number of observations | 365 | 406 | 409 | 408 | 400 |
| T-test results | | | | | |
| t-criterion | 2.12 | 0.59 | -1.88 | 0.15 | -1.21 |
| t-critical (p=0,95) | 1,96 | | | | |
| Null hypothesis | Rejected | Accepted | Accepted | Accepted | Accepted |

**Table C.2: T-test of the Day of the Week Effect for LiteCoin**

| Parameter | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| Population 1 (data without day of analysis) | | | | | |
| Mean,% | 0.62% | 0.75% | 0.39% | 0.56% | -0.16% |
| Standard deviation,% | 9.79% | 7.56% | 9.24% | 8.25% | 6.87% |
| Number of observations | 365 | 406 | 409 | 408 | 400 |
| T-test results | | | | | |
| t-criterion | 0.34 | 0.77 | -0.08 | 0.27 | -1.51 |
| t-critical (p=0,95) | 1,96 | | | | |
| Null hypothesis | Accepted | Accepted | Accepted | Accepted | Accepted |

**Table C.3: T-test of the Day of the Week Effect for Ripple**

| Parameter | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| Population 1 (data without day of analysis) | | | | | |
| Mean,% | 0.26% | 0.83% | 0.41% | 1.04% | 0.86% |
| Standard deviation,% | 7.80% | 8.61% | 6.35% | 9.21% | 7.04% |
| Number of observations | 365 | 406 | 409 | 408 | 400 |
| T-test results | | | | | |
| t-criterion | -0.94 | 0.32 | -0.75 | 0.73 | 0.46 |
| t-critical (p=0,95) | 1,96 | | | | |
| Null hypothesis | Accepted | Accepted | Accepted | Accepted | Accepted |

**Table C.4: T-test of the Day of the Week Effect for Dash**

| Parameter | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|
| Population 1 (data without day of analysis) | | | | | |
| Mean,% | 1.00% | 0.39% | 1.12% | 1.69% | 1.40% |
| Standard deviation,% | 20.11% | 11.01% | 8.26% | 8.70% | 8.04% |
| Number of observations | 365 | 406 | 409 | 408 | 400 |
| T-test results | | | | | |
| t-criterion | -0.11 | -1.20 | 0.01 | 1.12 | 0.59 |
| t-critical (p=0,95) | 1,96 | | | | |
| Null hypothesis | Accepted | Accepted | Accepted | Accepted | Accepted |

## Appendix D

### Parametric tests: ANOVA

**Table D.1: ANOVA test of the Day of the Week Effect for BitCoin**

| | F | p-value | F critical | Null hypothesis |
|---|---|---|---|---|
| Overall | 1.78 | 0.13 | 2.38 | Accepted |
| Monday | 4.29 | 0.04 | 3.86 | Rejected |
| Tuesday | 0.29 | 0.59 | 3.86 | Accepted |
| Wednesday | 2.99 | 0.08 | 3.86 | Accepted |
| Thursday | 0.02 | 0.89 | 3.86 | Accepted |
| Friday | 1.26 | 0.26 | 3.86 | Accepted |

**Table D.2: ANOVA test of the Day of the Week Effect for LiteCoin**

| | F | p-value | F critical | Null hypothesis |
|---|---|---|---|---|
| Overall | 0.41 | 0.80 | 2.38 | Accepted |
| Monday | 0.11 | 0.74 | 3.86 | Accepted |
| Tuesday | 0.49 | 0.48 | 3.86 | Accepted |
| Wednesday | 0.01 | 0.94 | 3.86 | Accepted |
| Thursday | 0.06 | 0.80 | 3.86 | Accepted |
| Friday | 1.77 | 0.18 | 3.86 | Accepted |

**Table D.3: ANOVA test of the Day of the Week Effect for Ripple**

| | F | F critical | p-value | Null hypothesis |
|---|---|---|---|---|
| Overall | 0.37 | 0.83 | 2.38 | Accepted |
| Monday | 0.76 | 0.38 | 3.86 | Accepted |
| Tuesday | 0.08 | 0.78 | 3.86 | Accepted |
| Wednesday | 0.40 | 0.53 | 3.86 | Accepted |
| Thursday | 0.43 | 0.51 | 3.86 | Accepted |
| Friday | 0.16 | 0.69 | 3.86 | Accepted |

**Table D.4: ANOVA test of the Day of the Week Effect for Dash**

| | F | F critical | p-value | Null hypothesis |
|---|---|---|---|---|
| Overall | 0.30 | 0.88 | 2.38 | Accepted |
| Monday | 0.01 | 0.92 | 3.87 | Accepted |
| Tuesday | 0.97 | 0.33 | 3.87 | Accepted |
| Wednesday | 0.00 | 0.99 | 3.87 | Accepted |
| Thursday | 0.85 | 0.36 | 3.87 | Accepted |
| Friday | 0.24 | 0.63 | 3.87 | Accepted |

## Appendix E

### Non-parametric tests: Kruskal -Wallis test

**Table E.1: Kruskal -Wallis test of the Day of the Week Effect for BitCoin**

| Parameter | Overall | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|---|
| Adjusted H | 6.39 | 8.67 | 1.52 | 3.26 | 0.60 | 0.07 |
| d.f. | 4 | 1 | 1 | 1 | 1 | 1 |
| P value: | 0.17 | 0.00 | 0.22 | 0.07 | 0.44 | 0.79 |
| Critical value | 9,48 | 3,84 | 3,84 | 3,84 | 3,84 | 3,84 |
| Null hypothesis | Accepted | Rejected | Accepted | Accepted | Accepted | Accepted |

**Table E.2: Kruskal -Wallis test of the Day of the Week Effect for LiteCoin**

| Parameter | Overall | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|---|
| Adjusted H | 1.70 | 0.07 | 0.00 | 1.47 | 0.00 | 1.15 |
| d.f. | 4 | 1 | 1 | 1 | 1 | 1 |
| P value: | 0.79 | 0.79 | 0.98 | 0.23 | 0.96 | 0.28 |
| Critical value | 9,48 | 3,84 | 3,84 | 3,84 | 3,84 | 3,84 |
| Null hypothesis | Accepted | Accepted | Accepted | Accepted | Accepted | Accepted |

**Table E.3: Kruskal -Wallis test of the Day of the Week Effect for Ripple**

| Parameter | Overall | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|---|
| Adjusted H | 1.64 | 0.64 | 1.07 | 0.62 | 1.00 | 0.33 |
| d.f. | 4 | 1 | 1 | 1 | 1 | 1 |
| P value: | 0.80 | 0.42 | 0.30 | 0.43 | 0.32 | 0.57 |
| Critical value | 9,48 | 3,84 | 3,84 | 3,84 | 3,84 | 3,84 |
| Null hypothesis | Accepted | Accepted | Accepted | Accepted | Accepted | Accepted |

**Table E.4: Kruskal -Wallis test of the Day of the Week Effect for Dash**

| Parameter | Overall | Monday | Tuesday | Wednesday | Thursday | Friday |
|---|---|---|---|---|---|---|
| Adjusted H | 6.50 | 2.39 | 5.11 | 1.96 | 0.10 | 0.02 |
| d.f. | 4 | 1 | 1 | 1 | 1 | 1 |
| P value: | 0.16 | 0.12 | 0.02 | 0.16 | 0.75 | 0.89 |
| Critical value | 9,48 | 3,84 | 3,84 | 3,84 | 3,84 | 3,84 |
| Null hypothesis | Accepted | Accepted | Rejected | Accepted | Accepted | Accepted |

## Appendix F

## Regression analysis with dummy variables

**Table F.1: Regression analysis with dummy variables of the Day of the Week Effect for crypto currencies (BitCoin, LiteCoin, Ripple and Dash)***

| Parameter | BitCoin | LiteCoin | Ripple | Dash |
|---|---|---|---|---|
| Monday ($a_0$) | 0.0091<br>(0.002) | 0.0062<br>(0.265) | 0.00264<br>(0.623) | 0.00943<br>(0.217) |
| Tuesday ($a_1$) | -0.0044<br>(0.299) | 0.0014<br>(0.863) | 0.00564<br>(0.457) | -0.00381<br>(0.725) |
| Wednesday ($a_2$) | -0.0104<br>(0.014) | -0.0023<br>(0.773) | 0.00147<br>(0.846) | 0.00416<br>(0.700) |
| Thursday ($a_3$) | -0.0054<br>(0.209) | -0.0006<br>(0.935) | 0.00776<br>(0.307) | 0.00650<br>(0.547) |
| Friday ($a_4$) | -0.0086<br>(0.044) | -0.0078<br>(0.321) | 0.00596<br>(0.433) | 0.00268<br>(0.804) |
| F-test | 1,78 (0.13) | 0,41 (0.80) | 0.37 (0.8285) | 0.27 (0.8975) |
| Multiple R | 0,08 | 0,04 | 0,04 | 0,03 |
| Anomaly | Confirmed | Not confirmed | Not confirmed | Not confirmed |

* P-values are in parentheses