PRICE OVERREACTIONS

IN THE CRYPTOCURRENCY MARKET

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Abstract

This paper examines price overreactions in the case of the cryptocurrencies with the highest market capitalisation and the longest span of data, namely BitCoin, LiteCoin, Ripple and Dash, over the period 2013-2017. A number of parametric (t-test, ANOVA, regression analysis with dummy variables) and non-parametric (Mann–Whitney U test) tests confirm the presence of price patterns after overreactions: the next-day price changes in both directions are bigger than after "normal" days. A trading robot approach is then used to establish whether these statistical anomalies can be exploited to generate profits. The results suggest that a strategy based on counter-movements after overreactions is not profitable, whilst one based on inertia appears to be profitable but produces outcomes not statistically different from the random ones. Therefore the overreactions detected in the cryptocurrency market do not give rise to exploitable profit opportunities (possibly because of transaction costs) and cannot be seen as evidence against the Efficient Market Hypothesis (EMH).

Keywords: *cryptocurrency market, Bitcoin, overreaction, momentum, abnormal returns, contrarian strategy, trading strategy, trading robot*

JEL classification: G12, G17, C63

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1. Introduction

The dominant paradigm in financial economics is still the Efficient Market Hypothesis (EMH) that implies that the behaviour of asset prices should be unpredictable (Fama, 1965). However, cognitive biases (Akerlof and Shiller, 2009), different investment horizons (Campbell and Viceira, 2002), noise traders (Black, 1985), the belief of many traders in technical analysis (Taylor and Allen, 1992) and other factors can generate so-called market anomalies, namely certain patterns in price behaviour making prices predictable (at least in the short run).

The most known market anomalies are calendar and size anomalies, price bubbles, M&A and IPO effects, momentum effects and contrarian trading, over- and underreactions etc. One of the most explored among them is the overreaction anomaly, which was first detected by De Bondt and Thaler (1985), who showed that the best (worst) performing portfolios in the NYSE over a three-year period normally under (over)-performed over the following three-years. In other words, there were identifiable patterns in price behaviour: after a significant growth corrections should be expected.

Despite a significant number of studies on market overreactions (De Bondt and Thaler, 1985; Brown et al., 1988; Atkins and Dyl, 1990; Bremer and Sweeney, 1991; Ferri and Min, 1996; Choi and Jayaraman, 2009; Mynhardt and Plastun 2013; Caporale et al., 2017; and many others) none of them has focused on the cryptocurrency market, which is the most volatile among financial markets: the average daily price amplitude in this market is more than 10 times higher than in FOREX, 7 times higher than in stock market and more than 5 times higher than in the commodity markets (see Appendix F for details). This feature (combined with the fact that it is a very young market) makes it particularly interesting to examine for possible overreactions.

This paper provides new evidence on the overreaction anomaly in the cryptocurrency market by testing the following two hypotheses: after one-day abnormal price movements (overreactions), on the next day abnormal price (i) counter-movements or (ii) momentum movements are observed. For this purpose, a number of statistical tests (both parametric and non-parametric) are carried out. A trading robot approach is then used to investigate whether any detected anomalies generate exploitable profit opportunities. The analysis is carried out for four different cryptocurrencies (BitCoin, LiteCoin, Ripple and Dash).

The remainder of the paper is organised as follows. Section 2 reviews the existing literature on the overreaction hypothesis. Section 3 describes the methodology used in this study. Section 4 discusses the empirical results. Section 5 provides some concluding remarks.

2. Literature Review

Following the already mentioned study by De Bondt and Thaler (1985), many other papers have tested the overreaction hypothesis, according to which if investors overreact in a given period, in the next period they move in the opposite direction; in the case of short-term overreactions one-day price increases are followed by price falls on the next day and vice versa. For example, Bremer and Sweeney (1991) showed that, after negative daily changes exceeding 10%, price increases on the next day averaged 1.77% (see also Caporale et al., 2017).

Market overreactions were found not only in stock markets (Brown et al., 1988; Atkins and Dyl, 1990; Larson and Madura, 2003 and many others), but also in the FOREX (Mynhardt and Plastun, 2013) and commodity markets (Cutler et al., 1991). Possible reasons for overreactions are discussed by Plastun (2017). These are psychological (cognitive traps, emotions and other psychological biases), technical (execution of stop losses and margin-calls, the use of technical analysis by traders), related to fundamentals (price-ratio hypothesis) etc.

As already pointed out, the cryptocurrency market is extremely volatile (see Dwyer. 2014); Cheung et al., 2015; Carrick , 2016). Bartos (2015) also reported that it immediately reacts to the arrival of new information and can therefore be as indirect evidence in favour of its efficiency. Similar conclusions were reached by Kurihara and Fukushima (2017), whilst Caporale and Plastun (2017) found evidence of a day-of-the-week anomaly. A different approach to testing market efficiency is to examine the possibility of generating abnormal profits. To do this in the current paper a trading robot method will be used. Of course, as shown by Atkins and Dyl (1990), incorporating transaction costs into the analysis may dramatically change the results, with abnormal returns becoming very small and statistically insignificant. Therefore our analysis incorporates the most significant component of transaction costs (the spread).

3. Data and Methodology

To analyse overreactions in the cryptocurrency market we use daily data on the four cryptocurrencies (BitCoin, LiteCoin, Ripple and Dash) with the highest market capitalisation and longest span of data, namely 28.04.2013-31.12.2017. The data source is CoinMarketCap (https://coinmarketcap.com/coins/). CoinMarketCap calculates prices as the volume-weighted average of all prices reported for each market. For example, BitCoin prices are the average of those from 400 markets.

MacKinlay and Richardson (1991) used the Generalized Method of Moments (GMM) to estimate the expected returns and the cumulative abnormal returns and analyse overreactions. In this paper we carry out instead a number of statistical tests, both parametric (in the case of normally distributed data) and non-parametric (in the case of non-normal distributions); they include Student's t-tests, ANOVA analysis, and Mann–Whitney U tests. The data are divided into two groups, one including observations after one-day abnormal price changes, the other after a day with normal price changes. The null hypothesis to be tested is that they are both drawn from the same population. If they are not, we can conclude that a statistical anomaly is present.

We also run multiple regressions with dummy variables and carry out average analysis. The regressions are specified as follows:

$$\mathrm{Y_t = a_0 + a_1 D_{1t} + \varepsilon_t} \qquad (1)$$

where Y_t – returns on day *t;*

$\mathrm{a_n}$– mean return on a normal day (a day when there was no overreaction);

D_{nt} – a dummy variable for a specific data group, equal to 1 when the data concern an overreaction day, and equal to 0 when they do not;

ε_t – Random error term at time *t*.

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

According to the overreaction hypothesis, after a day of overreaction there should be a correction, i.e. price counter-movements that are bigger than after normal days. This will be our Hypothesis 1 (H1): Counter-reactions after overreactions differ from those after normal days. However, there might be cases when one day is not enough to overreact; then after an overreaction day we can expect movements in the direction of the overreaction bigger than after normal days. This will be our Hypothesis 2 (H2): Price movements after overreactions in the direction of the overreaction differ from such movements after normal days.

If the results of the statistical tests for H1 or H2 point to statistical anomalies, then we apply a trading robot method to establish whether the detected anomalies create exploitable profit opportunities. This approach incorporates transaction costs such as spread, fees and commissions to brokers, bank payments etc., and simulates the actions of a trader according to an algorithm (trading strategy) such that the trading robot fully replicates the actions of market traders, therefore any abnormal profits made by exploiting the detected anomalies would represent evidence against the EMH. The trading robot is a program in the MetaTrader terminal developed in MetaQuotes Language 4 (MQL4).

To test whether the results we obtain differ from random ones t-tests are carried out. Specifically, two samples are created, one including results from the trading strategy, another randomly generated trading results. The null hypothesis (H0) is that both data sets belong to the same population, and the alternative (H1) that they do not. If H0 is rejected we can conclude that the results from the trading strategy are not random and therefore this strategy can generate abnormal profits.

To detect overreactions we follow Caporale et al. (2017), whose approach is consistent with the methodology to identify positive and negative shocks proposed by Lasfer et al. (2003). Therefore returns are calculated as follows:

$$R_i = \frac{(High_i - Low_i)}{Low_i} \times 100\%, \tag{2}$$

where R_i is the % daily return, $High_i$ is the maximum price, and Low_i is the minimum price for day i.

We use high/low parameters instead of standard open/close because differences between the maximum and minimum prices show the amplitude of the movement during the trading session and are more appropriate when analysing market overreactions.

An overreaction is described by the following inequality:

$$R_i > (\overline{R}_n + k \times \delta_n), \tag{3}$$

where k is the number of standard deviations used to identify the overreaction,

$\overline{R}_n$ is the average size of daily returns for period n

$$\overline{R}_n = \sum_{i=1}^{n} R_i / n \tag{4}$$

and δ_n is the standard deviation of daily returns for period n

$$\delta_n = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (R_i - \overline{R})^2} \ . \tag{5}$$

The next step is to determine the size of the price movement during the next day. For Hypothesis 1 (the counter-reaction or counter-movement assumption), we measure it as the difference between the next day’s open price and the maximum deviation from it in the opposite direction to the price movement on the overreaction day.

If the price increased, then the size of the counter-reaction is calculated as:

$$cR_{i+1} = 100\% \times \frac{(Open_{i+1} - Low_{i+1})}{Low_{i+1}}, \tag{6}$$

where cR_{i+1} is the counter-reaction size, and $Open_{i+1}$ is the next day's open price.

If the price decreased, then the corresponding definition is:

$$cR_{i+1} = 100\% \times \frac{(High_{i+1} - Open_{i+1})}{Open_{i+1}}. \tag{7}$$

In the case of Hypothesis 2 (movement in the direction of the overreaction), either equation (7) or (6) is used depending on whether the price has increased or decreased.

4. Empirical Results

A key issue when examining overreactions is how they are defined - for example, as a 10% price change in Bremer and Sweeney (1991). It should be mentioned that using a constant value may lead to biased results (see Cox and Peterson, 1994 for details). To avoid this trap in this paper a dynamic approach is used: overreactions are defined on the basis of the number of standard deviations to be added to the average return. However, these are influenced by the averaging period, therefore there are two parameters to be chosen on the basis of preliminary calculations.

First we analyse the number of days when returns differ from their mean value using different averaging periods (5, 10, 20, 30, 40 and 50) and different number of standard deviations. The results are presented in Table 1.

Table 1: Number of overreactions detected in Bitcoin prices during 2013-2017

Period of averaging	5		10		20		30		40		50	
Indicator	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%
Overall	1600	100	1595	100	1585	100	1575	100	1565	100	1555	100
Number of abnormal returns (criterion =mean+sigma_dz)	296	19	267	17	241	15	243	15	236	15	227	14
Number of abnormal returns (criterion= mean+2*sigma_dz)	0	0	101	6	128	8	124	8	106	7	103	7
Number of abnormal returns (criterion = mean+3*sigma_dz)	0	0	0	0	73	5	71	5	63	4	58	4

As can be seen, each additional standard deviation significantly decreases the number of observed overreactions. The sample size is critical for statistical testing, and therefore the most appropriate number of standard deviations to be added to the average is 1. Table 1 gives no clear answer concerning the optimal averaging period. That is why additional calculations are needed.

To show that counter-reactions after the day of the overreaction differ from those for normal days Student's t–tests can be used. The null hypothesis is that the two data sets belong to the same general population. In particular we carry out Student's t–tests of the counter-reactions after the day of the overreaction for Bitcoin prices over the period 2013-2017 (see Tables 2 and 3) for the different averaging period. The results suggest that the optimal averaging periods starts from 5 (since this value null hypothesis is rejected).

Table 2: T-test of the counter-reactions after the day of the overreaction for the Bitcoin prices during 2013-2017 for the averaging periods 5, 10, 20

Period	5		10		20	
Parameter	Normal	Overreaction	Normal	Overreaction	Normal	Overreaction
Mean	2.13%	2.98%	2.01%	3.53%	2.00%	3.71%
Standard deviation	3.48%	5.27%	3.22%	6.00%	3.23%	6.18%
Number of values	1303	296	1327	267	1342	241
t-criterion	2.65		4.02		4.19	
t-critical (p=0.95)	1.96		1.96		1.96	
Null hypothesis	rejected		rejected		rejected	

Table 3: T-test of the counter-reactions after the day of the overreaction for the Bitcoin prices during 2013-2017 for the averaging periods 30, 40, 50

Period	30		40		50	
Parameter	Normal	Overreaction	Normal	Overreaction	Normal	Overreaction
Mean	1.96%	3.89%	1.94%	4.05%	1.92%	4.19%
Standard deviation	3.22%	6.15%	3.21%	6.22%	3.20%	6.30%
Number of values	1330	243	1327	236	1326	227
t-criterion	4.75		5.10		5.31	
t-critical (p=0.95)	1.96		1.96		1.96	
Null hypothesis	rejected		rejected		rejected	

To choose among averaging periods we test the trading strategy based on counter-reactions after the day of the overreaction with a different set of parameters (see Figure 1). The results provide evidence in favour of 30 as an appropriate value for the averaging period; they also corroborate the conclusion that the most appropriate number of standard deviations is 1.

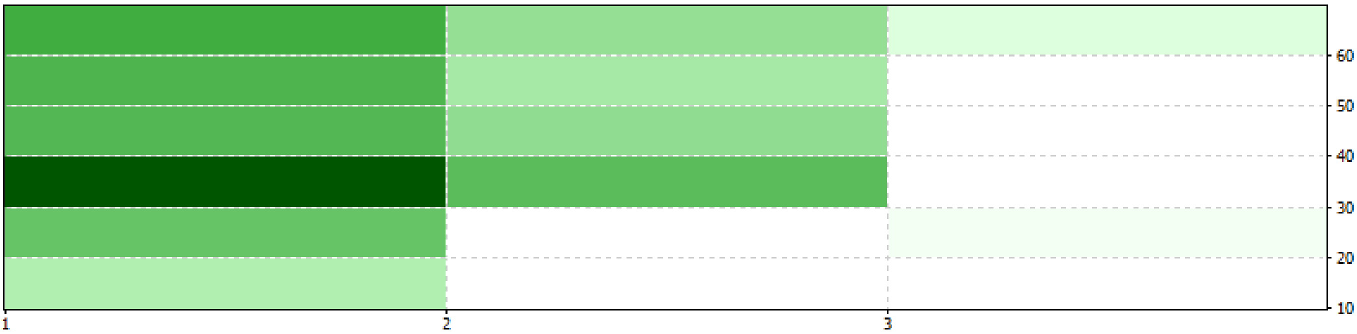

Figure 1: Testing results for the BitCoin, period 2017 (X – sigma_dz, Y – period_dz)*

* The darker the bars, the more profitable the trading strategy is.

The results for H1 and H2 are presented in Appendix B and C and are summarised in Tables 4 and 5.

Table 4: H1 test results: summary*

Hypothesis	BitCoin	LiteCoin	Ripple	Dash
Average analysis	+	+	+	+
T-test	+	+	+	+
ANOVA	+	+	+	+
Mann–Whitney U test	+	+	+	+
Regression analysis with dummy variable	+	+	+	+

* ”+” –hypothesis not rejected, “-” - hypothesis rejected.

Table 5: H2 test results: summary*

Hypothesis	BitCoin	LiteCoin	Ripple	Dash
Average analysis	+	+	+	+
T-test	+	+	+	+
ANOVA	+	+	+	+
Mann–Whitney U test	+	+	+	+
Regression analysis with dummy variable	+	+	+	+

* ”+” –hypothesis not rejected, “-” - hypothesis rejected.

As can be seen, neither hypothesis can be rejected, which confirms the presence of a statistical anomaly in price dynamics in the cryptocurrency market: after overreaction days price changes in both directions (in the direction of overreaction and counter movement) are bigger than after normal days.

Next we test whether these anomalies can be exploited to make abnormal profits by using a trading robot approach and considering 2 trading strategies. Strategy 1 is based on the standard overreaction anomaly: there are abnormal counter-reactions after the overreaction day. The trading algorithm in this case is specified as follows: the cryptocurrency is sold (bought) on the open price of the day after the overreaction if an abnormal price increase (decrease) has occurred. The open position is closed at the end of the day when it was opened. Strategy 2 is based on the momentum effect, the so-called "inertia anomaly" (see Caporale et al., 2017 for details): there are abnormal price movements in the direction of the overreaction on the following day. The trading algorithm is specified as follows: after the overreaction day the cryptocurrency is sold (bought) on the open price of the day after the overreaction if an abnormal price decrease (increase) has occurred. Again, an open position is closed at the end of the day when it was opened.

BitCoin prices are used for the analysis (data availability motivated this choice) for the years 2015, 2016, 2017 in turn and then for the whole period 2015-2017. An example of the strategy tester report is shown in Appendix D. The results of the trading robot analysis are presented in Table 6 (both for the Strategy 1 and 2). T-tests are carried out to establish whether or not these results are statistically different from the random ones (see Appendix E for details).

As can be seen, the results of Strategy 1 are rather stable and in general imply a lack of exploitable profit opportunities from trading based on counter-movements after overreactions in the cryptocurrency market. This applies to all periods.

Table 6: Trading results for Strategy 1 and 2, case of Bitcoin

Period	Parameters	Strategy 1	Strategy 2
2015	% successful	45.71%	51.16%
	profit, USD	-71.20	65.83
	number of trades	43	43
	t-test	failed	failed
2016	% successful	55.00%	47.50%
	profit, USD	-9.24	51.89
	number of trades	40	40
	t-test	failed	failed
2017	% successful	42.03%	58.33%
	profit, USD	-6201.85	5765.36
	number of trades	72	72
	t-test	failed	failed
2015-2017	% successful	46.53%	53.55%
	profit, USD	-6279.29	5879.08
	number of trades	155	155
	t-test	failed	failed

The t-test statistics indicate that the results are not significantly different from the random ones (see Appendix F for details); indirect evidence for this is also provided by the number of profitable trades, which is close to 50%. By contrast, Strategy 2 generates profits in each individual year as well as the full sample, but the results are not significantly different from the random ones (as implied by the t-test statistics). The number of profitable trades is close to 50%. Overall, trading based on the "inertia" anomaly cannot be considered profitable.

5. Conclusions

This paper examines price behaviour in the cryptocurrency market after one-day abnormal price changes (overreactions). Using data on the cryptocurrency markets that are most liquid and have the highest capitalisation (BitCoin, LiteCoin, Ripple and Dash) for the period 2013-2017 two different hypotheses were tested: counter-reactions after volatility explosions differ from those after normal days (H1) and price movements after volatility explosions in the same direction of the overreaction differ from those after normal days (H2). For this purpose a variety of statistical tests were performed, including average analysis, t-tests, ANOVA, regression analysis with dummy variables, Mann–Whitney U tests, etc. Neither hypothesis could be rejected, which implies that overreactions cause statistically abnormal price behaviour in the cryptocurrency market.

A trading robot approach was then applied to incorporate transaction costs into the analysis and investigate whether the detected anomalies can be exploited to make abnormal profits. Two different trading strategies were developed: Strategy 1, which is based on the assumption that after the overreaction day counter-movements are bigger than after a normal day and Strategy 2, based on the "inertia anomaly" (after the overreaction day price movements in the direction of the overreaction are bigger than after a standard day).

The trading stimulations suggest that Strategy 1 is unprofitable, i.e. the detected anomalies cannot be exploited to make abnormal profits; Strategy 2 generates stable profits but these are not statistically different from the random results, which again imply the absence of exploitable profit opportunities. Consequently, the existence of overreaction anomalies in the cryptocurrency market cannot be seen as evidence against the EMH.

To conclude, our analysis has shown that whether or not statistically significant anomalies can be exploited to generate abnormal profits by devising appropriate trading strategies crucially depends on transaction costs and their size. Admittedly, the current paper is only the first step in the exploration of the overreaction hypothesis in the cryptocurrency market. There now exist more than 1000 cryptocurrencies with different degrees of liquidity and a possibly different behaviour, with different implications for market efficiency. Future work will provide more evidence on these issues by examining a wider sample of cryptocurrencies.

Compliance with Ethical Standards

Conflict of Interest: Author **Guglielmo Maria Caporale** declares that he has no conflict of interest. Author **Alex Plastun** declares that he has no conflict of interest.

Ethical approval: This article does not contain any studies with human participants performed by any of the authors.

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Appendix A

Table A.1: T-test of the counter-reactions after the overreaction day for the BitCoin prices during 2013-2017: case of averaging period 5, 10 and 20 days

Period	5		10		20	
Parameter	Normal	Overreaction	Normal	Overreaction	Normal	Overreaction
Mean	2.13%	2.98%	2.01%	3.53%	2.00%	3.71%
Standard deviation	3.48%	5.27%	3.22%	6.00%	3.23%	6.18%
Number of values	1303	296	1327	267	1342	241
t-criterion	2.65		4.02		4.19	
t-critical (p=0.95)	1.96		1.96		1.96	
Null hypothesis	rejected		rejected		rejected	

Table A.2: T-test of the counter-reactions after the overreaction day for the BitCoin prices during 2013-2017: case of averaging period 30, 40 and 50 days

Period	30		40		50	
Parameter	Normal	Overreaction	Normal	Overreaction	Normal	Overreaction
Mean	1.96%	3.89%	1.94%	4.05%	1.92%	4.19%
Standard deviation	3.22%	6.15%	3.21%	6.22%	3.20%	6.30%
Number of values	1330	243	1327	236	1326	227
t-criterion	4.75		5.10		5.31	
t-critical (p=0.95)	1.96		1.96		1.96	
Null hypothesis	rejected		rejected		rejected	

Appendix B

Statistical tests of Hypothesis 1

Average analysis

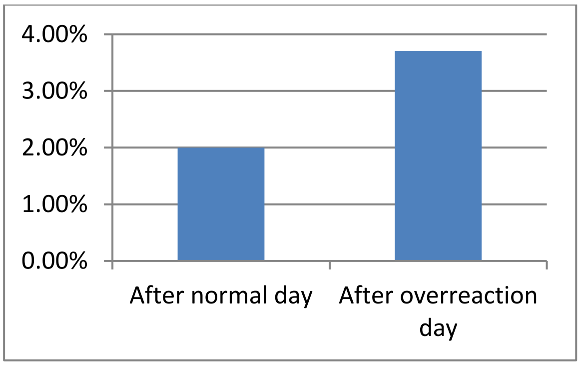

Figure B.1 – Average analysis case of BitCoin

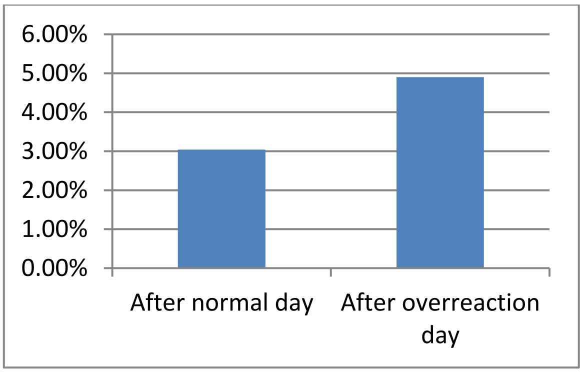

Figure B.2 – Average analysis case of LiteCoin

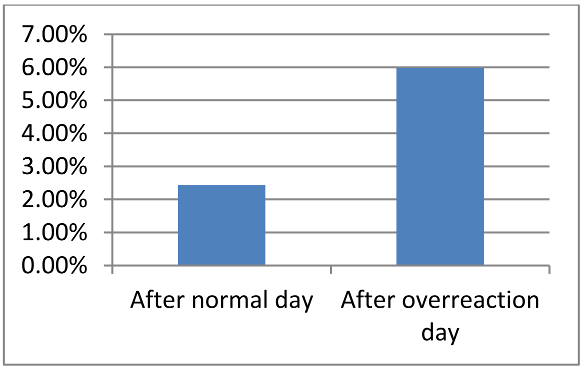

Figure B.3 – Average analysis case of Ripple

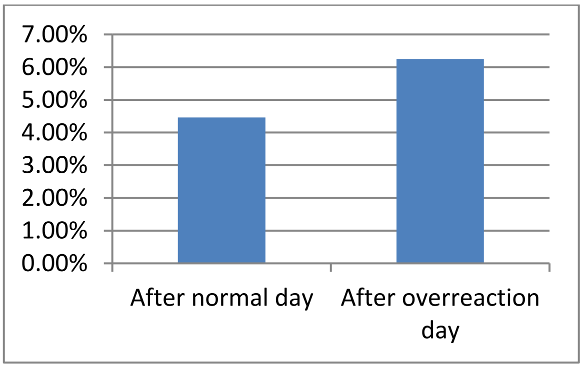

Figure B.4 – Average analysis case of Dash

Parametric tests: Student's t-test

Table B.1: T-test of Hypothesis 1 (averaging period = 30, number of standard deviations used to detect overreaction = 1)

Cryptocurrency	BitCoin		LiteCoin		Ripple		Dash	
Indicator	After normal day	After overreaction day	After normal day	After overreaction day	After normal day	After overreaction day	After normal day	After overreaction day
Mean	2.00%	3.71%	3.04%	4.90%	2.43%	5.98%	4.46%	6.25%
Standard deviation	3.24%	6.18%	6.27%	8.57%	4.24%	12.34%	7.29%	9.75%
Number of matches	1332	241	1369	203	1264	211	1083	198
t-criterion	4.19		2.97		4.13		2.46	
t-critical (p=0.95)	1.96		1.96		1.96		1.96	
Null hypothesis	rejected		rejected		rejected		rejected	

Parametric tests: ANOVA

Table B.2: ANOVA test of Hypothesis 1 (averaging period = 30, number of standard deviations used to detect overreaction = 1)

Hypothesis	BitCoin	LiteCoin	Ripple	Dash
F	40.99	26.72	62.01	9.29
P value	0.00	0.00	0.00	0.00
F critical	3.85	3.85	3.85	3.85
Null hypothesis	rejected	rejected	rejected	rejected

Non-parametric tests: Mann–Whitney U test

Table B.3: Mann–Whitney U test of Hypothesis 1 (averaging period = 30, number of standard deviations used to detect overreaction = 1)

Parameter	BitCoin	LiteCoin	Ripple	Dash
Adjusted H	31.47	30.78	25.71	15.14
d.f.	1	1	1	1
P value:	0.00	0.00	0.00	0.00
Critical value	3.84	3.84	3.84	3.84
Null hypothesis	rejected	rejected	rejected	rejected

Regression analysis with dummy variables

Table B.4: Regression analysis with dummy variables of Hypothesis 1 (averaging period = 30, number of standard deviations used to detect overreaction = 1)

Parameter	BitCoin	LiteCoin	Ripple	Dash
Mean volatility (a_0)	0.0200 (0.0000)	0.0304 (0.0000)	0.0243 (0.0000)	0.0446 (0.0000)
Dummy coefficient (a_1)	0.0172 (0.0000)	0.0188 (0.0001)	0.0357 (0.0000)	0.0182 (0.0023)
F-test	41.00 (0.0000)	14.28 (0.0001)	62.01 (0.0000)	9.29 (0.0023)
Multiple R	0.16	0.09	0.20	0.08
Anomaly	confirmed	confirmed	confirmed	confirmed

* P-values are in parentheses

Appendix C

Statistical tests of Hypothesis 2

Average analysis

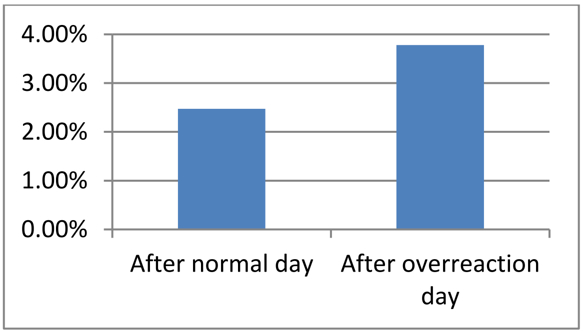

Figure C.1 – Average analysis case of BitCoin

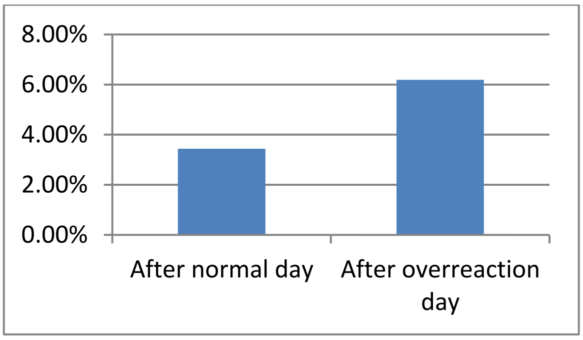

Figure C.2 – Average analysis case of LiteCoin

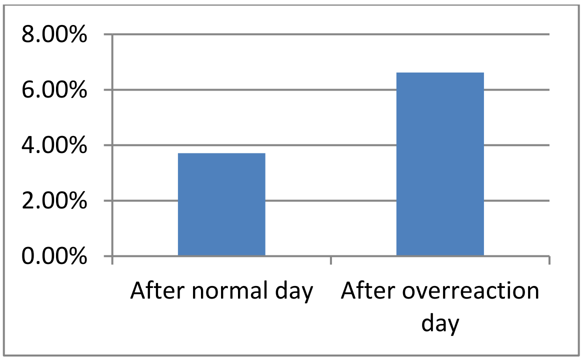

Figure C.3 – Average analysis case of Ripple

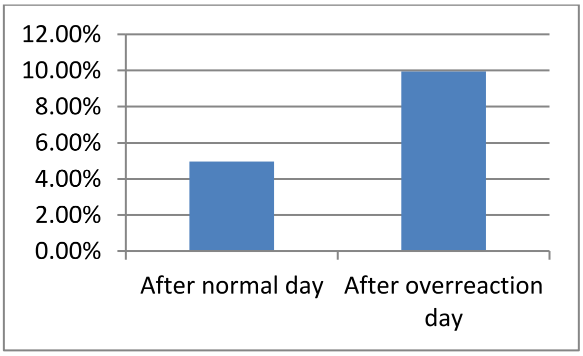

Figure C.4 – Average analysis case of Dash

Parametric tests: Student's t-test

Table C.1: T-test of Hypothesis 2 (averaging period = 30, number of standard deviations used to detect overreaction = 1)

Cryptocurrency	BitCoin		LiteCoin		Ripple		Dash	
Indicator	After normal day	After overreaction day	After normal day	After overreaction day	After normal day	After overreaction day	After normal day	After overreaction day
Mean	2.47%	3.78%	3.44%	6.19%	3.72%	6.62%	4.96%	9.94%
Standard deviation	4.01%	4.66%	6.68%	9.69%	8.92%	10.68%	14.41%	18.38%
Number of matches	1332	241	1369	203	1264	211	1083	198
t-criterion	4.09		3.90		3.74		3.62	
t-critical (p=0.95)	1.96		1.96		1.96		1.96	
Null hypothesis	rejected		rejected		rejected		rejected	

Parametric tests: ANOVA

Table C.2: ANOVA test of Hypothesis 2 (averaging period = 30, number of standard deviations used to detect overreaction = 1)

Hypothesis	BitCoin	LiteCoin	Ripple	Dash
F	21.06	26.72	18.40	18.58
P value	0.00	0.00	0.00	0.00
F critical	3.85	3.85	3.85	3.85
Null hypothesis	rejected	rejected	rejected	rejected

Non-parametric tests: Mann–Whitney U test

Table C.3: Mann–Whitney U test of Hypothesis 2 (averaging period = 30, number of standard deviations used to detect overreaction = 1)

Parameter	BitCoin	LiteCoin	Ripple	Dash
Adjusted H	34.00	28.53	25.63	36.72
d.f.	1	1	1	1
P value:	0.00	0.00	0.00	0.00
Critical value	3.84	3.84	3.84	3.84
Null hypothesis	Rejected	Rejected	Rejected	Rejected

Regression analysis with dummy variables

Table C.4: Regression analysis with dummy variables of Hypothesis 2 (averaging period = 30, number of standard deviations used to detect overreaction = 1)

Parameter	BitCoin	LiteCoin	Ripple	Dash
Mean volatility (a_0)	0.0247 (0.0000)	0.0344 (0.0000)	0.0372 (0.0000)	0.0496 (0.0000)
Dummy coefficient (a_1)	0.0132 (0.0000)	0.0277 (0.0000)	0.0293 (0.0000)	0.0502 (0.0000)
F-test	21.07 (0.0000)	26.72 (0.0000)	18.40 (0.0000)	18.58 (0.0000)
Multiple R	0.11	0.13	0.11	0.12
Anomaly	confirmed	confirmed	confirmed	confirmed

* P-values are in parentheses

Appendix D

Example of strategy tester report: case of BitCoin, period 2015, H2 testing

Table D.1: Overall statistics

Symbol		BTCUSD (1 Lot= 10 BTC)			
Period		Daily (D1) 2015.01.01 00:00 - 2015.12.31 00:00 (2015.01.01 - 2015.12.31)			
Model		Every tick (the most precise method based on all available least timeframes)			
Bars in test	1312	Ticks modelled	19794	Modelling quality	90.00%
Mismatched charts errors	0				
Initial deposit	10000.00			Spread	Current
Total net profit	65.83	Gross profit	252.96	Gross loss	-187.13
Profit factor	1.35	Expected payoff	1.53		
Absolute drawdown	57.58	Maximal drawdown	104.11 (1.04%)	Relative drawdown	1.04% (104.11)
Total trades	43	Short positions (won %)	17 (47.06%)	Long positions (won %)	26 (53.85%)
		Profit trades (% of total)	22 (51.16%)	Loss trades (% of total)	21 (48.84%)
	Largest	profit trade	50.65	loss trade	-37.91
	Average	profit trade	11.50	loss trade	-8.91
	Maximum	consecutive wins (profit in money)	6 (94.61)	consecutive losses (loss in money)	4 (-60.28)
	Maximal	consecutive profit (count of wins)	94.61 (6)	consecutive loss (count of losses)	-60.28 (4)
	Average	consecutive wins	2	consecutive losses	2

Figure D.1: Equity dynamics

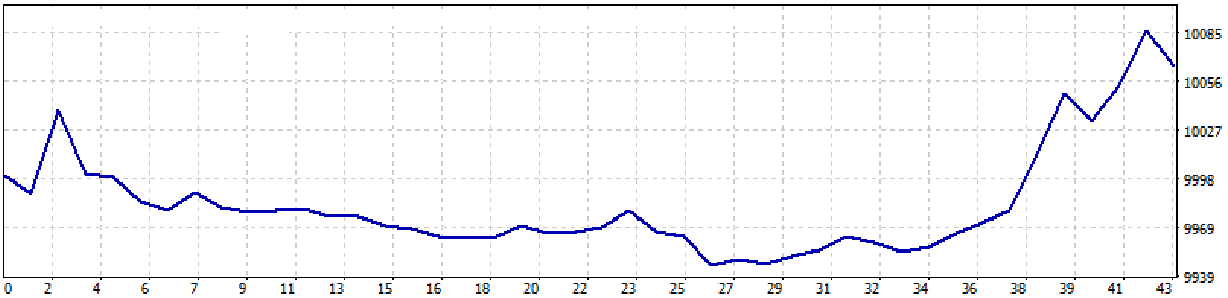

Table D.2: Statement (fragment)

#	Time	Type	Order	Size	Price	S / L	T / P	Profit	Balance
1	2015.01.08 00:00	buy	1	0.10	290.53	0.00	0.00		
2	2015.01.08 23:59	close	1	0.10	279.10	0.00	0.00	-11.43	9988.57
3	2015.01.14 00:00	sell	2	0.10	217.66	0.00	0.00		
4	2015.01.14 23:59	close	2	0.10	167.01	0.00	0.00	50.65	10039.22
5	2015.01.15 00:00	sell	3	0.10	166.43	0.00	0.00		
6	2015.01.15 23:59	close	3	0.10	204.34	0.00	0.00	-37.91	10001.31
7	2015.01.16 00:00	buy	4	0.10	204.36	0.00	0.00		
8	2015.01.16 23:59	close	4	0.10	201.87	0.00	0.00	-2.49	9998.82
9	2015.01.27 00:00	buy	5	0.10	260.27	0.00	0.00		
10	2015.01.27 22:13	close	5	0.10	246.09	0.00	0.00	-14.18	9984.64
11	2015.01.29 00:00	sell	6	0.10	221.41	0.00	0.00		
12	2015.01.29 22:20	close	6	0.10	227.11	0.00	0.00	-5.70	9978.94
13	2015.03.03 00:00	buy	7	0.10	267.50	0.00	0.00		
14	2015.03.03 22:20	close	7	0.10	278.68	0.00	0.00	11.18	9990.12
15	2015.03.04 00:00	buy	8	0.10	276.32	0.00	0.00		
16	2015.03.04 22:20	close	8	0.10	266.96	0.00	0.00	-9.36	9980.76
17	2015.03.05 00:00	sell	9	0.10	267.00	0.00	0.00		
18	2015.03.05 22:20	close	9	0.10	270.08	0.00	0.00	-3.08	9977.68
19	2015.03.06 00:00	buy	10	0.10	270.50	0.00	0.00		
20	2015.03.06 22:20	close	10	0.10	271.91	0.00	0.00	1.41	9979.09
21	2015.03.10 00:00	buy	11	0.10	284.62	0.00	0.00		
22	2015.03.10 22:13	close	11	0.10	285.50	0.00	0.00	0.88	9979.97
23	2015.03.19 00:00	sell	12	0.10	250.34	0.00	0.00		
24	2015.03.19 22:20	close	12	0.10	254.74	0.00	0.00	-4.40	9975.57
25	2015.03.25 00:00	sell	13	0.10	244.73	0.00	0.00		
26	2015.03.25 22:20	close	13	0.10	244.55	0.00	0.00	0.18	9975.75
27	2015.04.28 00:00	buy	14	0.10	232.64	0.00	0.00		
28	2015.04.28 22:20	close	14	0.10	226.67	0.00	0.00	-5.97	9969.78
29	2015.05.01 00:00	buy	15	0.10	236.48	0.00	0.00		
30	2015.05.01 22:40	close	15	0.10	234.30	0.00	0.00	-2.18	9967.60
31	2015.06.02 00:00	sell	16	0.10	222.70	0.00	0.00		
32	2015.06.02 22:20	close	16	0.10	226.60	0.00	0.00	-3.90	9963.70
33	2015.06.17 00:00	buy	17	0.10	248.97	0.00	0.00		
34	2015.06.17 22:20	close	17	0.10	247.76	0.00	0.00	-1.21	9962.49
35	2015.06.18 00:00	sell	18	0.10	247.40	0.00	0.00		
36	2015.06.18 22:20	close	18	0.10	247.26	0.00	0.00	0.14	9962.63
37	2015.06.30 00:00	buy	19	0.10	254.92	0.00	0.00		
38	2015.06.30 22:20	close	19	0.10	261.72	0.00	0.00	6.80	9969.43
39	2015.07.01 00:00	buy	20	0.10	260.84	0.00	0.00		
40	2015.07.01 22:20	close	20	0.10	256.74	0.00	0.00	-4.10	9965.33
41	2015.07.02 00:00	sell	21	0.10	255.19	0.00	0.00		
42	2015.07.02 22:13	close	21	0.10	254.30	0.00	0.00	0.89	9966.22
43	2015.07.14 00:00	sell	22	0.10	285.75	0.00	0.00		
44	2015.07.14 22:20	close	22	0.10	283.18	0.00	0.00	2.57	9968.79
45	2015.08.19 00:00	sell	23	0.10	227.22	0.00	0.00		
46	2015.08.19 22:20	close	23	0.10	216.82	0.00	0.00	10.40	9979.19
47	2015.08.20 00:00	sell	24	0.10	217.15	0.00	0.00		
48	2015.08.20 22:20	close	24	0.10	229.82	0.00	0.00	-12.67	9966.52
49	2015.08.21 00:00	buy	25	0.10	229.74	0.00	0.00		
50	2015.08.21 22:13	close	25	0.10	226.55	0.00	0.00	-3.19	9963.33

Appendix E

t-tests for trading results

Table E.1: t-test for trading results: case of Strategy 1

Parameter	2015	2016	2017	2015-2017
Number of the trades	43	40	72	155
Total profit	-71.2	-9.24	-6201.85	-6279.29
Average profit per trade	-2.0	-0.2	-89.9	-43.6
Standard deviation	16.8	21.4	488.5	341.3
t-test	-0.72	-0.07	-1.53	-1.53
t critical (0,95)	1.68	1.68	1.66	1.66
Null hypothesis	confirmed	confirmed	confirmed	confirmed

Table E.2: t-test for trading results: case of Strategy 2

Parameter	2015	2016	2017	2015-2017
Number of the trades	43	40	72	155
Total profit	65.83	51.89	5765.36	5879.08
Average profit per trade	1.53	1.30	80.07	37.93
Standard deviation	15.39	20.02	476.37	327.27
t-test	0.65	0.41	1.42	1.44
t critical (0,95)	1.68	1.68	1.66	1.66
Null hypothesis	confirmed	confirmed	confirmed	confirmed

Appendix F

Comparative analysis of average daily price amplitude in different financial markets

Table F.1: Comparative analysis of average daily price amplitude in different financial markets

Instrument	Market	2014	2015	2016	2017	Average
EURUSD	FOREX	0.6%	1.1%	0.8%	0.6%	0.8%
Dow-Jones Industrial	Stock Market	0.8%	1.2%	1.0%	0.5%	0.9%
CSI300		1.5%	3.0%	1.5%	0.9%	1.8%
Gold	Commodities	1.3%	1.4%	1.5%	0.9%	1.3%
Oil		1.8%	3.9%	3.9%	2.1%	2.9%
BitCoin	Cryptocurrency	5.0%	4.2%	2.4%	6.3%	5.1%
LiteCoin		6.6%	6.4%	2.9%	9.6%	7.3%
Dash		22.0%	9.0%	7.1%	11.3%	12.1%
Ripple		7.1%	4.2%	3.2%	12.7%	7.3%

Figure F.1: Visualization of comparative analysis