Department of
Economics and Finance

Working Paper No. 18-05

Economics and Finance Working Paper Series

Guglielmo Maria Caporale, Alex Plastun,
Viktor Oliinyk

Bitcoin Fluctuations and the Frequency Of Price Overreactions

September 2018

http://www.brunel.ac.uk/economics

BITCOIN FLUCTUATIONS

AND THE FREQUENCY OF PRICE OVERREACTIONS

Guglielmo Maria Caporale*
Brunel University London, CESifo and DIW Berlin

Alex Plastun**
Sumy State University

Viktor Oliinyk
Sumy State University

September 2018

Abstract

This paper investigates the role of the frequency of price overreactions in the cryptocurrency market in the case of BitCoin over the period 2012-2018. Specifically, it uses a static approach to detect overreactions and then carries out hypothesis testing by means of a variety of statistical methods (both parametric and non-parametric) including ADF tests, Granger causality tests, correlation analysis, regression analysis with dummy variables, ARIMA and ARMAX models, neural net models, and VAR models. Specifically, the hypotheses tested are whether or not the frequency of overreactions (i) is informative about Bitcoin price movements (H1) and (ii) exhibits seasonality (H2). On the whole, the results suggest that it can provide useful information to predict price dynamics in the cryptocurrency market and for designing trading strategies (H1 cannot be rejected), whilst there is no evidence of seasonality (H2 is rejected).

Keywords: cryptocurrency, Bitcoin, anomalies, overreactions, abnormal returns, frequency of overreactions

JEL classification: G12, G17, C63

*Corresponding author. Department of Economics and Finance, Brunel University, London, UB8 3PH.

Email: Guglielmo-Maria.Caporale@brunel.ac.uk

**The second-named author gratefully acknowledges financial support from the Ministry of Education and Science of Ukraine (0117U003936).

1. Introduction

Cryptocurrencies have attracted considerable attention since their recent creation and experienced huge swings. For instance, in 2017 Bitcoin prices rose by more than 20 times, but in early 2018 fell by 70%; similar sharp drops had in fact already occurred 5 times before (June 2011, January 2012, April 2013, November 2013, December 2017). Such significant deviations of asset prices from their average values during certain periods of time are known as overreactions and have been widely analysed in the literature since the seminal paper of De Bondt and Thaler (1985), various studies being carried out for different markets (stocks, FOREX, commodities etc.), countries (developed and emerging), assets (stock prices/indices, currency pairs, oil, gold etc.) and time intervals (daily, weekly, monthly etc.). However, hardly any evidence is available to date on the cryptocurrency market, which is particularly interesting because of its very extremely high volatility compared to the FOREX or stock market (

et al., 2015 and Dwyer, 2015). Also, its average daily price amplitude is up to 10 times higher than in the FOREX or stock market (see Table 1).

Table 1: Comparative analysis of the 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.	

The static approach was introduced by Sandoval and Franca (2012) and developed by Caporale and Plastun (2018). Returns are defined as:

$$5_{ç} = \ln(2_{ç}) \; F \ln(2_{ç?5}) \qquad (1)$$

where $5_{ç}$ stands for returns, and $2_{ç}$ and $2_{ç?5}$ are the close prices of the current and previous day. The next step is analysing the frequency distribution by creating histograms. We plot values 10% above or below those of the population. Thresholds are then obtained for both positive and negative overreactions, and periods can be identified when returns were above or equal to the threshold.

Such a procedure generates a data set of the frequency of overreactions (at a monthly frequency), which is then divided into 3 subsets including respectively the frequency of negative and positive overreactions, and of them all. In this study we also use an additional measure (named the "Overreactions multiplier"), namely the negative/positive overreactions ratio:

$$1 R A N N A = ? Q H E L A H \frac{Ù å Ø æ Ø á Ö ìâ Ù á Ø Ù Ô é Ü á é Ø å å Ø â Ô á Ø ç Ü}{Ù å Ø æ Ø á Ö ìâ Ù ãâ æ Ü çâ Ü é Ø å å Ø â Ô á Ø ç Ü} \qquad (2)$$

Then the following hypotheses are tested:

Hypothesis 1 (H1): The frequency of overreactions is informative about price movements in the cryptocurrency market.

There is a body of evidence suggesting that typical price patterns appear in financial markets after abnormal price changes. The relationship between the frequency of overreactions and BitCoin prices is investigated by running the following regressions (see equations 3 and 4):

$$Y_r = a_4 + a_5^{>} D_{5r}^{>} + a_5^{-} D_{5r}^{-} + B_r \qquad (3)$$

where ;$_{ç}$ – BitCoin log differences on day t;

a_l – BitCoin mean log differences;

=

=

Information criteria, specifically AIC (Akaike, 1974) and BIC (Schwarz, 1978), are used to select the best ARMAX specification for BitCoin log returns.

As a robustness check, VAR models are also estimated:

$$\sum_{i=1}^{p} \quad t-i \quad t$$

Table 2: Results of ANOVA and non-parametric Kruskal-Wallis tests for statistical differences in the frequency of overreactions between different years

ANOVA test			
F	p-value	F critical	Null hypothesis
7.24	0.000	2.81	Rejected
Kruskal-Wallis test			
Adjusted H	p-value	Critical value	Null hypothesis
14.98	0.001	9.49	Rejected

Next we carry out correlation analysis. Table 3 reports the results for different parameters (number of negative overreactions, number of positive overreactions, overall number of overreactions and overreactions multiplier) and indicators (BitCoin close prices, BitCoin returns, BitCoin log returns)

Table 3: Correlation analysis between the frequency of overreactions and different BitCoin series

Parameter	BitCoin close prices	BitCoin returns	BitCoin log returns
Over_negative	0.50	-0.21	-0.34
Over_positive	0.41	0.62	0.53
All_over	0.53	0.25	0.13
Over_mult	0.15	-0.40	-0.60

There appears to be a positive (rather than negative, as one would expect) correlation between BitCoin prices and negative overreactions. By contrast, there is a negative correlation in the case of returns and log returns. The overreaction multiplier exhibits a rather strong negative correlation with BitCoin log returns. Finally, the overall number of overreactions has a rather weak correlation with prices.

To make sure that there is no need to shift the data in any direction we carry out a cross-correlation analysis of these indicators at time intervals t

Figure 1: Cross-correlation between Bitcoin log returns and frequency of overreactions over the whole sample period for different leads and lags

To analyse further the relationship between BitCoin log returns and the frequency of overreactions we carry out ADF tests on the series of interest (see Table 4).

Table 4: Augmented Dickey-Fuller test: BitCoin log returns and overreactions frequency data*

Parameter	logreturns	Over_all	Over_negative	Over_positive
Augmented Dickey-Fuller test (Intercept)				
Augmented Dickey-Fuller test statistic	-7.55	-2.87	-5.48	-3.39
Probability	0.0000	0.0549	0.0000	0.0152
Test critical values (5% level):	-2.89	-2.89	-2.89	-2.89

(see Section 3 for details) The results for BitCoin closes, returns and log returns are regressed against all overreactions, negative and positive overreactions presented in Table 5, 6, and 7 respectively.

Table 5: Regression analysis results: BitCoin closes

Parameter	all overreactions	negative and positive overreactions as separate variables	regression with dummy variables
$=_4$	-100.64 (0.85)	-158.22 (0.77)	368.88 (0.32)
Slope for the overreactions (? = CKAB= HKHR A N N A ⇒ ? P E K	350.77 (0.00)	-	-
Slope for the overreactions (? = CKAB JAC= P E KRA A N N A ⇒ ?	-	475.44 (0.00)	551.28 (0.00)
Slope for the overreactions (? = CKAB L K O E KRA A N N A ⇒ ?	-	237.43 (0.10)	514.33 (0.00)
F-test	22.55 (0.00)	11.69 (0.00)	16.32 (0.00)
Multiple R	0.53	0.54	0.46

* P-values are in parentheses

Table 6: Regression analysis results: BitCoin returns

Parameter	all overreactions	negative and positive overreactions as separate variables	regression with dummy variables
$=_4$	-0.0442(0.72)	0.0395 (0.55)	0.0119(0.88)
Slope for the overreactions (? = CKAB= HKHR A N N A ⇒ ? P E K	0.0328(0.00)	-	-
Slope for the overreactions (? = CKAB JAC= P E KRA A N N A ⇒ ?	-	-0.1597(0.00)	0.0023(0.00)
Slope for the overreactions (? = CKAB L K O E KRA A N N A ⇒ ?	-	0.2076(0.00)	0.0922(0.00)
F-test	3.93(0.05)	77.64 (0.00)	8.71(0.00)
Multiple R	0.25	0.86	0.36

* P-values are in parentheses

Table 7: Regression analysis results: BitCoin log returns

Parameter	all overreactions	negative and positive overreactions as separate variables	regression with dummy variables
$=_4$	-0.0200(0.72)	0.0645 (0.04)	0.0368 (0.35)
Slope for the overreactions (? = CKAB= HKHR A N N A ⇒ ? P E K	0.0084 (0.33)	-	-
Slope for the overreactions (? = CKAB JAC= P E KRA A N N A ⇒ ?	-	-0.0939(0.00)	-0.0122(0.32)

Slope for the overreactions

(? = CKABL K O E IR RE RA AN N A) ? I - 0.1013(0.00)

Table 8: Comparative characteristics of neural networks

Architecture	Performance			Errors		
	Learning	Control	Test	Learning	Control	Test
MLP 2-2-3-1:1	0.4484	0.4547	0.5657	0.0811	0.0392	0.0630
L 2-2-1:1	0.3809	0.6265	0.8314	0.0664	0.0801	0.0836

Table 9: Quality comparison of neural networks

Parameters	Type of neural net

suggests that the regression model (eq. 8) captures very well the behaviour of BitCoin prices.

We also estimate ARIMA(p,d,q) models with $p \le 3$; $q \le 3$; $d \ge 0$ choosing the best specification on the basis of the AIC and BIC information criteria. Specifically, we select the following models: ARIMA(2,0,2) (on the basis of the AIC criterion); ARIMA (1,0,0) and ARIMA(0,0,1) (on the basis of the BIC criterion). The p

$a_{t\ 3}$

As can be seen, the null hypothesis of no causality is rejected for negative (OF-) and positive overreactions (OF+), but not for BitCoin log returns (r), and therefore there is evidence that forecasts of the latter can be imp88 c6983(nd)0.5b05 Tw [(i

This model appears to be data congruent: it is stable (no root lies outside the unit circle), and there is no evidence of autocorrelation in the residuals. The IRF analysis (see Appendix C, Figures C.13-C.3 for details) shows that, in response to a -1 standard deviation shock to log returns, both negative (OF^-) and positive overreactions (OF^+) revert to their equilibrium value within six periods, whereas it takes log returns only one period to revert to equilibrium. There is hardly any response of log returns to shocks to either positive or negative overreactions, whils both the latter variables tend to settle down after about six periods.

The variance decomposition (VD) analysis (see Table 15) suggests the following:

Table 15: Variance Decomposition

Variable	Lag	Percentage of the variance accounted for by a variable		
		Y	OF^+	OF^-
Y	1	100.00	0.00	0.00
	2	97.42	0.19	2.39
	3 >	97.42	0.19	2.39
OF^+	1	17.04	82.96	0.00
	2	22.02	77.98	0.00
	3 >	22.65	76.74	0.61
OF^-	1	36.13	38.65	25.22
	2	37.58	41.79	20.63
	3 >	36.86	43.04	20.10

The behaviour of Y is mostly explained by its previous dynamics (97.4%); OF^+ accounts for only 0.2 % of its variance and OF^- only 2.4%;

The behaviour of OF^+ is also mainly determined by its previous dynamics (76.7%), with Y explaining only 22.7 % of its variance and OF^- only 0.6%;

The behaviour of OF^- is mostly accounted for by the OF^- dynamics (43%), with Y explaining 36.9% of its variance and OF^+ 20.1%.

Finally, we address the issue of seasonality (H2). Figure 5 suggests that the overreactions frequency tends to be higher at the end and the start of the year and lower at other times. Also, there appears to be a mid-year cycle: the frequency starts to increase in April, peaks in June-July and then falls till September with a “W” seasonality pattern.

Figure 5: Monthly seasonality in the overreaction frequency

Formal parametric (ANOVA) and non-parametric (Kruskal-Wallis) tests are performed; the results are presented in Tables 16 and 17.

Table 16: Parametric ANOVA of monthly seasonality in the

As can be seen, there are no statistically significant differences between the frequency of overreactions in different months of the year (i.e. no evidence of seasonality), therefore H2 can be rejected, which is consistent with the visual evidence based on Figure 3.

5. Conclusions

This paper investigates the role of the frequency of price overreactions in the cryptocurrency market in the case of BitCoin over the period 2013-2018. Specifically, it uses a static approach to detect overreactions and then carries out hypothesis testing by means of a variety of statistical methods (both parametric and non-parametric) including ADF tests, Granger causality tests, correlation analysis, regression analysis with dummy variables, ARIMA and ARMAX models, neural net models, and VAR models. Specifically, the hypotheses tested are whether or not the frequency of overreactions (i) is informative about Bitcoin price movements (H1) and (ii) exhibits seasonality (H2).

On the whole, the results suggest that the frequency of price overreactions can provide useful information to predict price dynamics in the cryptocurrency market and for designing trading strategies (H1 cannot be rejected) in the specific case of BitCoin. However, these findings are somewhat mixed: stronger evidence of a predictive role for the frequency of price overreactions is found when estimating neural net and ARMAX models as opposed to VAR models. As for the possible presence of seasonality, the evidence is very clear: no seasonal patterns are detected for the frequency of price overreactions (H2 is rejected).

Wong, M., (1997), Abnormal Stock Returns Following Large One

Appendix A

Frequency distribution of BitCoin

TableA.1: Frequency distribution of BitCoin, 2013-2018*

Plot	Frequency
<-0.04	181
-0.03	75
-0.02	96
-0.01	164
0	331

Appendix B

Frequency of overreactions

Table B.1: Frequency of overreaction over the period 2013-2018, annual*

Year	Negative over	Positive over	All over	Mult
2013	29	41	70	0.7
2014	35	22	57	1.6
2015	25	21	46	1.2
2016	11	11	22	1.0
2017	50	53	103	0.9
2018	30	19	49	1.6
Mean	30	30	60	1.1
Std. Dev.	12.7	15.2	26.8	0.32

Figure B.1: Frequency of overreactions: dynamic analysis over the period 2013-2018, annual data*

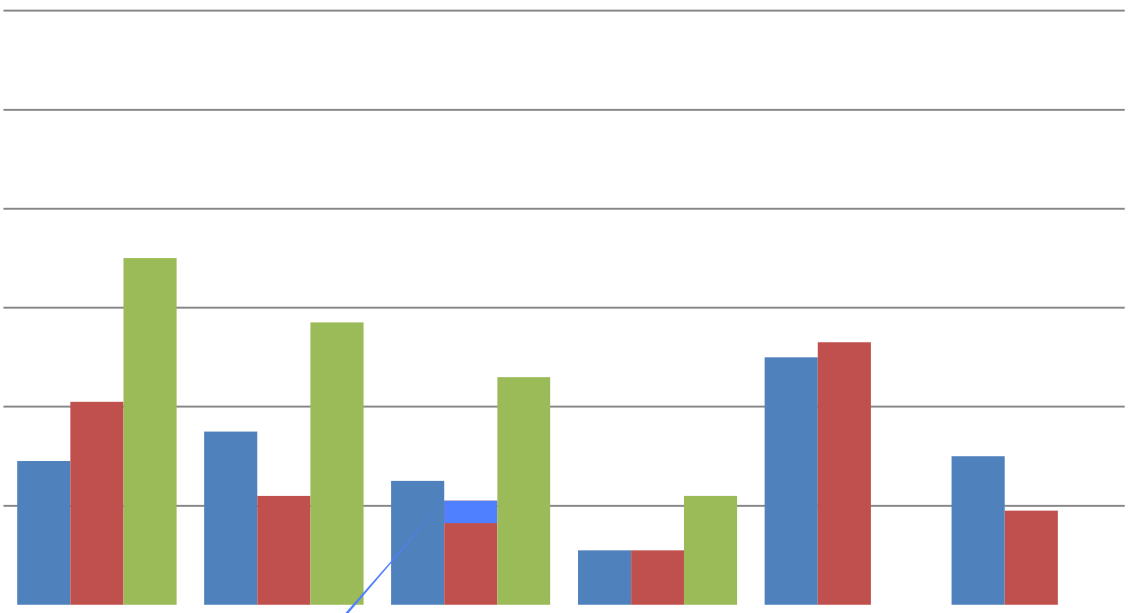
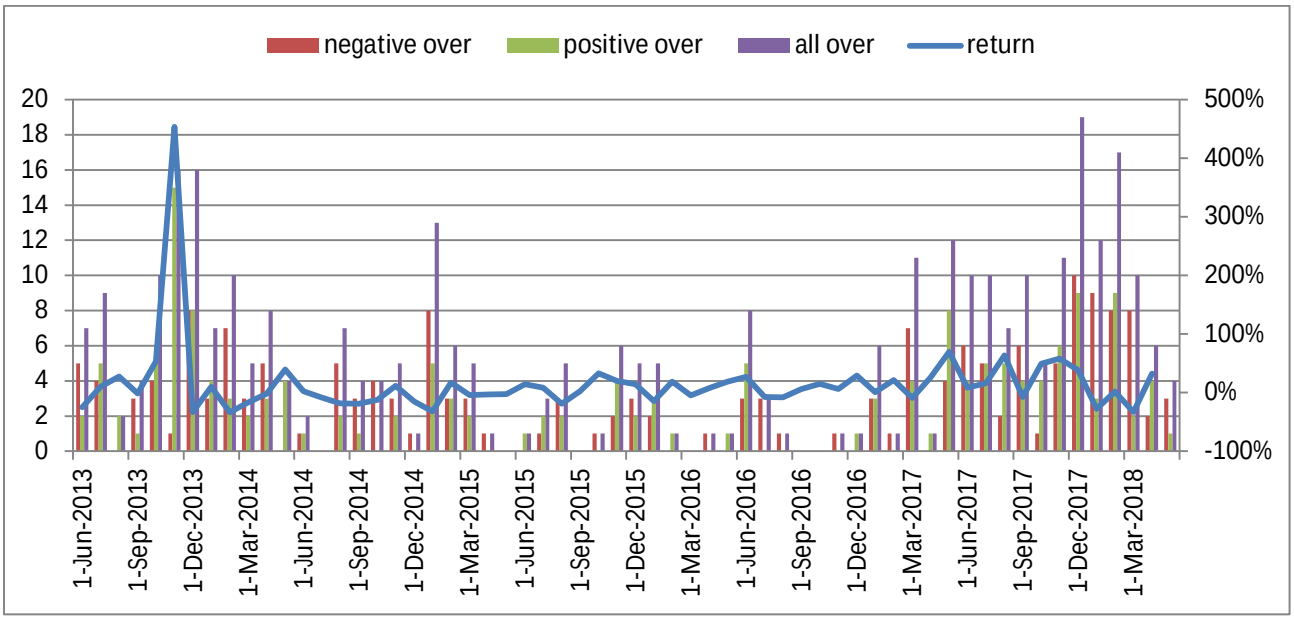


Figure B.2: Frequency of overreactions: dynamic analysis over the period 2013-2018, monthly data*



* 2013 data start on 01.05.2013; 2018 data end on 31.05.2018

Appendix C

Impulse response function (IRF) analysis: log returns (Y)-D; negative overreactions (OF-)- E; positive overreactions (OF+)-F

Figure C.1: Re(on-82.(Tc -0.<</MCEs 0Chart 1 >>BDC 1090.004 Tc4T0 1 T1313(8 17

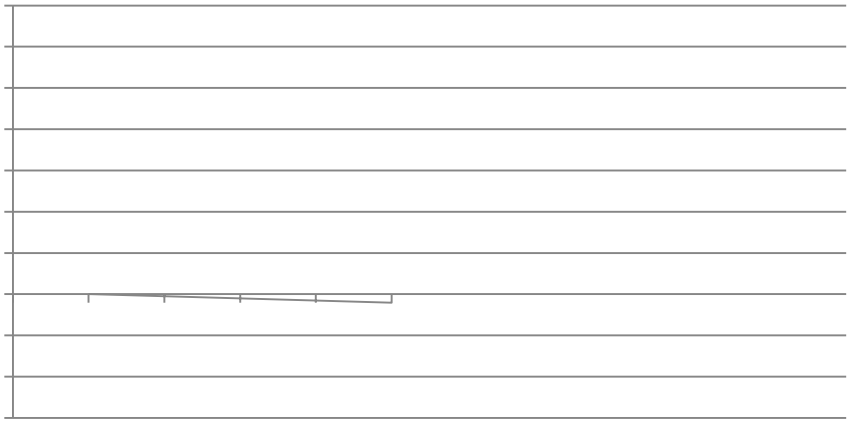



Figure C.3: Response to a 1-standard deviation shock to positive overreactions