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# Cryptic Currencies: Bitcoin at its Peak

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## Abstract

The cryptocurrencies are digital currencies that were initially designated to replace the old ones. However, they act as investment assets and many treat them like stocks. The market for cryptocurrencies counts more than 1600 types and the Bitcoin is the first and foremost of all of them. In one year the price of Bitcoin grew staggering 2000 percent. Other currencies have not seen this type of rising. This study investigates the period of over 4 years of data for 5 cryptocurrencies, the three years before and the last year of hyper-growth of the Bitcoin. We used GARCH model to see if two periods of data may offer some incites for patterns. The findings of this paper show that the Bitcoin in the period of high volatility is more diverged from its counterparts. According to results in the period of high volatility, the factors that influence the price formation of cryptocurrencies may not be the same for all of them. Using the price of the Bitcoin of one day earlier and the price of altcoins today we find spillover effect. Spillover effect is less prominent in the second period of high volatility. It may indicate of relatively independent nature of altcoins during the periods of high volatility.

## 1. INTRODUCTION

In 2018 a word cryptocurrency does not surprise anyone anymore. Progress is fast indeed, a great information exchange capabilities of the modern world are able to acquaint even such a complex thing as “blockchain” with anyone and make it a common sense. The Bitcoin has been open to the public since 2009 and nine years later, it had an unprecedented price tag for its kind. Beginning as a currency plan Bitcoin has quickly become an investment instrument. Many studies confirm that the cryptocurrencies behave more as investment assets rather than currencies. This makes them be treated as stocks, but with an additional feature – anyone can mine them.

As a leader of cryptocurrencies, the Bitcoin mainly earned its place in the market due to its early launch, the first coin. From the start, it steadily began to climb up and provoked competitors to arise. Geek generation of digital market embraced the idea of blockchain and rapidly flooded the market with hundreds of other cryptocurrencies. So-called “altcoins” are mainly based on the system of the bitcoin; however, all strive to eliminate the shortcomings and outperform their ancestor in one or the other way. Still, Bitcoin remains the most popular and expensive currency at the time.

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It is presumed that as a currency the most popular coin will stay popular and get even more popular, nevertheless, the transition from one to another currency does not require much (Gandal and Halaburda, 2016). No ID, difficult manipulations, or extended period of time is needed to sell Bitcoins and hop on another more promising coin.

The trends of cryptocurrency went that far, even well-known companies attempting to ride the wave. Corbet et al., (2018) investigate in their work how Kodak, a company that went bankrupt after the inept adoption of digital photography at its birth, is making an announcement of releasing KODACoin and receiving positive corrections on their shares on the stock market. This is another way of exploiting the trend of financial bubbles.

## 2. LITERATURE REVIEW

The cryptocurrencies in spite of their name barely hold qualities of currencies. As the initial proposition of Bitcoin it was supposed to be an international independent decentralized currency and in some cases it still is. However, much literature on cryptocurrencies found the similarities with investment assets and how traders, specifically starting from the buzz around the Bitcoin and its continuous price rise, treat them. Taken as an investment Bitcoin is put in comparison even such giants as S&P500 and its resemblance of a stock is being proven many times (Wong et al., 2018).

The major divergence of virtual currencies from usual investments like stocks is the possibility of acquiring them by mining. Mining a coin is a full-time job for some and allows doing so with a room of high-end powerful computers with immensely strong computing capabilities. This according to Eyal and Sirer, (2014) opens the opportunities for so-called “selfish miners” to mine more than others. Incentive-compatibility does not hold true in this case. These tendencies could lead to turning the majority of users to follow such “selfish” strategy. Studies have shown that many do not use mined coins as currency in its old-fashion way, most of the mined cryptocurrencies stay at their mined base or moved to some saving accounts (Ron and Shamir, 2013). It is another reason to think of cryptocurrencies as the investment, therefore treat them and measure with tools that are designed for measuring stocks would not be a mistake.

Introduced as currencies cryptocurrencies should and do act in developed countries as assets that can be exchanged for goods. Simulating stocks cryptocurrencies still can be as good as any countries national currency. On the contrary, stocks cannot be exchanged for goods and do not function as currencies. A stock is an investment asset that may become more valuable if the company that it belongs to performs better and raises its value. However, as the investment the bitcoin and altcoins appear to have a speculative nature (Yermack, 2015), which is predominantly different from economic assets. The cryptocurrencies have no intrinsic value except the demand it generated due to impressive popularity. The value that is so important for investment assets’ core characteristic is fragile and appears to be ephemeral. This feature of being speculative is alarming in terms of risk management. This seemingly transient quality lays risks and some studies baptized the cryptocurrencies as another financial bubble (Cheah and Fry, 2015). Some confirmed the speculative features using ARMA models (MacDonell, 2014). The ARMA model is frequently used in studies of stock exchanges and price-volatile markets that is a plausible reason for us to apply the same model style in this study.

## 3. DATA AND METHODS

The main cryptocurrency in this study is Bitcoin and it is put in the center of the matter for its enormous share of volume of market capitalization compared to other cryptocurrencies. Also, the price of Bitcoin could be a significant driver for other coins to follow or imitate. Looking at a graph of several cryptocurrencies with Bitcoin in it, one could say that there is an obvious pattern according to which altcoins tend to mimic the movements of the Bitcoin. It is fair to assume that this duplicating is not necessarily the same across all time. Specifically, in the times of high volatility compared to times of low volatility these patterns could change. Certainly, there is plethora of factors to affect the prices of cryptocurrencies that would dilute the results’ significance; however, we believe that other reasons should be considered in another more thorough study.

As this work is being written the prices of Bitcoin and altcoins have changed, that is not reflected in our data. The full data is starting from July 2014 and ends in January 2018. We split the data into two periods where the splitting point lies on January 2017. The first period of relatively low volatility consists of a sample of 941 observations. The second more volatile period has a sample of 381 observations. It is important to note that the cryptocurrencies were chosen with the widest timescale that would allow such a range of observation over 1300 combined. Prices of these coins are very different[1] compared to one another.

Bitcoin leads with an extremely high price tag, the others’ prices are more than modest. Nevertheless, all used currencies find their positions on top of charts by market capitalization and volume. In addition, our choice fell on this group of altcoins to capture more observations. These are the ones that had data over 4 years that was suitable for our research.

The two periods are considered to have a qualitatively different composition. The first period is referred to as a relatively quiet and low volatile where the second period is more dynamic and higher in volatility. These two periods are regarded as slightly different for the reasons related to Bitcoin’s rapid change in price. The second period of our data starts count of the price for the Bitcoin to climb unprecedentedly high marks, from the beginning of the year with near $1000 USD till its climax of $20,000 USD per coin at the end of the year. Such a drastic behavior change in a period of one year cannot go by unnoticed which has brought the cryptocurrency topic to masses and drew the attention of millions.

We collected data for several cryptocurrencies from the *coindesk.com* and applied a log return formula to measure price changes. Our list of coins

[1] The prices of coins from our sample at the moment of writing are: Bitcoin – $7,723; Ripple – $0.6837; Litecoin – $122; Monero – $170; Dash – 318. (coincharts.info)

includes Bitcoin, Monero, Dash, Ripple, and Litecoin.

$$R_{j,t} = \ln\left(\frac{P_{j,t}}{P_{j,t-1}}\right) \tag{1}$$

Where $P_{j,t}$ is a closing price for the trading day *j*. For the regression model we base on (Rachev et al., 2007) paired with autoregressive moving average (ARMA) and generalized autoregressive moving average (GARCH) models.

ARMA (g,s) - GARCH (p,q)

$$R_{i,t}^{c} + \mathrm{h}_{\mathrm{i,t}}^{\mathrm{c}} = \alpha_0 + \alpha_1 R_t^{bit} + \alpha_2 R_{t-1}^{bit} + \alpha_3 \sum_{i=1}^{g} R_{i,t-i}^{c} + \alpha_4 \sum_{i=1}^{s} \varepsilon_{i,t-i}^{c} + \alpha_5 \sum_{i=1}^{p} \varepsilon_{i,t-i}^{c^2} + \alpha_6 \sum_{i=1}^{q} h_{i,t-i}^{c} + \varepsilon_{i,t}^{c} \tag{2}$$

Where:

$\varepsilon_{\mathrm{i,t}}^{\mathrm{c}} \sim \mathrm{N}(0, \mathrm{h}_{\mathrm{i,t}}^{\mathrm{c}})$ – error term with mean zero and variance one;

$R_{i,t}^{c}$ – cryptocurrency returns at the period *t*;

$\alpha_1 R_t^{bit}$ – bitcoin return on period *t*;

$\alpha_2 R_{t-1}^{bit}$ – bitcoin return on period *t-1*;

$\alpha_3 \sum_{i=1}^{g} R_{i,t-i}^{c}$ – higher order of the autoregressive AR(g) for cryptocurrency returns at the period *t*;

$\alpha_4 \sum_{i=1}^{s} \varepsilon_{i,t-i}^{c}$ – higher order moving average mean process MA(s) for cryptocurrency returns at the period *t*;

$\alpha_5 \sum_{i=1}^{q} \varepsilon_{i,t-i}^{c^2}$ – q order of the ARCH term for cryptocurrency returns at the period *t*;

$\alpha_6 \sum_{i=1}^{p} h_{i,t-i}^{c}$ – p order conditional heteroscedasticity of GARCH term for cryptocurrency returns at period *t*;

$\varepsilon_{i,t}^{c}$ – Cryptocurrency returns residual at the period *t*.

With this set, we will run a regression of GARCH function and pairs of cryptocurrencies with Bitcoin as an independent variable in two different periods. As it was said earlier the Bitcoin is a ruler of this study and we measure all other altcoins' behavior against it. We believe that as the strongest cryptocurrency the Bitcoin is playing a role of driver or influential counterpart that could not be neglected when studying altcoins. The major objective of this work is to find altcoins' price change in two periods: the first is where the Bitcoin is relatively steady; the second period where the Bitcoin is aggressive and highly priced. It is expected to have the two periods to have distinctive patterns for the altcoins to be related with the Bitcoin.

We use the lagged variable of Bitcoin for the spillover effect on altcoins. The Bitcoin (t-1) represents a price of Bitcoin the day before. The prices of cryptocurrencies mimic each other that means there are common factors that influence all of them together. To see how one cryptocurrency may affect others we should use the observation of that particular coin the day before. This way it will be logical to conclude that some of the change was made by the price of the yesterday's cryptocurrency price, in our case it is Bitcoin.

## 4. RESULTS AND DISCUSSION

The unit root test for cryptocurrencies using Augmented Dickey-Fuller test aims to check the conditions of stationarity and having a unit root that would go into conflict with the consistency of data for ARMA modeling. The results of both first and second periods of our data suggest that null hypothesis which is existing unit root and non-stationarity is rejected therefore we proceed to ARMA. The ADF test is followed by a test for serial correlation that we run through Breusch-Godfrey Serial Correlation test that showed us insignificant results which support a proposition of failing to reject the null hypothesis of having a serial correlation on each cryptocurrency. Finally, we test for heteroscedasticity with Chi-Square test and again all results demonstrate significant findings that mean that observations have heteroscedasticity and an ARCH LM effect (Table 1).

The use of the ARMA model is to identify if there is an autoregressive pattern and moving average processes. The first part of the equation is to determine if there is autoregression which means the variable affects its own future self. The moving average is used to characterize shock information in a series, such as unexpected announcements or drastic changes. But these combinations of two cannot be used to capture volatility clustering since their conditional variance is constant. Therefore we need to use a GARCH model. GARCH outcome is significant on Bitcoin shows a positive response to shocks and lags of the period (-1) in both periods of our sample. We assume that the Bitcoin is likely to go up when the preceding day has seen growth. In other words Bitcoins, growth is partially due to its own spillover effect.

In the paired time series regression of all altcoins against the Bitcoin one by one and its lagged effect, we distinguish several findings that may indicate of an existing pattern in two different periods (Table 3). Bitcoin (-1) that stands for t-1 which is a closing price for the day before. This way we can see the spillover effect of Bitcoin and its influence on the behavior of altcoins to it. In our results, we distinguish a present spillover effect of yesterday's Bitcoin on today's altcoins. The other important result is that two periods have slightly different patterns that we would like to think are a reason of high fluctuations of the Bitcoin.

**Table 1.**
Preliminary tests for ARMA (Numbers in parentheses show significance level)

| | | Augmented Dickey-Fuller | | Breusch-Godfrey Serial Correlation LM Test | | Heteroscedasticity |
|---|---|---|---|---|---|---|
| | | ADF 1% Level | prob. | F-statistic | LM | Obs*R-squared |
| 1st period | Bitcoin | -24.32413 | 0.00 | 1.818221(0.16) | 3.649473(0.16) | 129.3159(0.00) |
| | Litecoin | -24.09694 | 0.00 | 0.256468(0.77) | 0.517051(0.77) | 29.18948(0.00) |
| | Ripple | -26.61255 | 0.00 | 0.544883(0.58) | 1.097814(0.57) | 52.17298(0.00) |
| | Monero | -29.38407 | 0.00 | 1.060971(0.34) | 2.137564(0.34) | 24.22222(0.00) |
| | Dash | -32.14167 | 0.00 | 0.421342(0.65) | 0.846915(0.65) | 115.693(0.00) |
| 2nd period | Bitcoin | -18.8341 | 0.00 | 0.068804(0.93) | 0.140068(0.93) | 14.25124(0.00) |
| | Litecoin | -18.72955 | 0.00 | 0.130148(0.87) | 0.233543(0.88) | 6.34669(0.00) |
| | Ripple | -11.84285 | 0.00 | 0.079017(0.92) | 0.161284(0.92) | 38.10591(0.00) |
| | Monero | -21.53944 | 0.00 | 0.519392(0.59) | 1.05249(0.59) | 6.923404(0.00) |
| | Dash | -20.2668 | 0.00 | 0.119306(0.88) | 0.242257(0.88) | 4.338346(0.00) |

**Table 1**
Presence of ARMA, GARCH effects with AIC in two periods

| | 1st period | | | 2nd period | | |
|---|---|---|---|---|---|---|
| | ARMA | GARCH | AIC | ARMA | GARCH | AIC |
| Bitcoin | (2,2) | (3,3) | -4.899687 | (2,2) | (1,1) | -3.591809 |
| Litecoin | (3,2) | (1,3) | -4.3946895 | (2,3) | (2,3) | -2.55305 |
| Ripple | (3,2) | (2,1) | -3.682582 | (3,2) | (2,3) | -2.345114 |
| Monero | (3,3) | (3,2) | -2.705771 | (1,2) | (2,1) | -2.643327 |
| Dash | (3,3) | (3,1) | -3.300751 | (0,3) | (1,3) | -2.471183 |

* AIC - Akaike info criterion

The main findings of this study are shown in Table 3. The Bitcoin's price on the day before against altcoins' today's price one by one. On the first period has a positive coefficient of 0.21 that is the highest among all altcoins. Also, Litecoin in the first period shows the highest level of significance of lower than 1 percent. Every one unit of the Bitcoin change we see 0.21 increase in Litecoin. The Ripple coin shows a negative coefficient of -0.087 for a one unit change of Bitcoin. Dash also has a negative coefficient of -0.088 which is very similar to the Ripple. Unfortunately, the outcome of Monero did not have significant indicator, therefore, we skip it.

On the second period Litecoin has a coefficient of 0.15 for every unit change of Bitcoin. The significance level fell to 5 percent. The altcoins Ripple and Dash have no significant results in the second period. But the Monero is contrary significant and has a coefficient of 0.15 for every unit Bitcoin's change.

These findings indicate that in the first period the three out of four altcoins show significant results. In the second period, the two out of three altcoins lose their significant indicators. In the second period, the altcoins seem to be freer from Bitcoin's fluctuations and influence. Monero was not significant in the first period and became significant in the second period. The periods of are only distinctive by the volatility level of Bitcoin. Bitcoin in the second period is less correlated with altcoins. Bitcoin and altcoins have diverged from being in one segment of cryptocurrencies. It means the factors that influence Bitcoins are not the same that influence altcoins. This suggests that independent from the Bitcoin altcoins could find their own niche

**Table 3.**
Paired regression with independent variable Bitcoin (t-1) against every altcoin in two periods

| | 1st period | | | | | 2nd period | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Variable | Coefficient | Std. Error | z-Statistic | Prob. | Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| **Litecoin** | C | -0.000949 | 0.001254 | -0.756736 | 0.4492 | C | 0.003646 | 0.004001 | 0.911399 | 0.3621 |
| | BITCOIN (-1) | 0.21449 | 0.051543 | 4.161351 | 0.0000 | BITCOIN (-1) | 0.159971 | 0.073302 | 2.182351 | 0.0291 |
| | R-squared | 0.007794 | | | | R-squared | 0.021392 | | | |
| | Adjusted R-squared | 0.001413 | | | | Adjusted R-squared | 0.005608 | | | |
| **Ripple** | C | -0.003392 | 0.001165 | -2.910851 | 0.0036 | C | -0.00334 | 0.002586 | -1.291252 | 0.1966 |
| | BITCOIN (-1) | -0.08766 | 0.040901 | -2.143229 | 0.0321 | BITCOIN (-1) | -0.059119 | 0.040427 | -1.462359 | 0.1436 |
| | R-squared | 0.00867 | | | | R-squared | -0.084253 | | | |
| | Adjusted R-squared | 0.002295 | | | | Adjusted R-squared | -0.101788 | | | |
| **Dash** | C | 0.000109 | 0.001311 | 0.083337 | 0.9336 | C | 0.012414 | 0.004912 | 2.52709 | 0.0115 |
| | BITCOIN (-1) | -0.088414 | 0.046991 | -1.881502 | 0.0599 | BITCOIN(-1) | -0.11601 | 0.101333 | -1.144848 | 0.2523 |
| | R-squared | 0.013308 | | | | R-squared | -0.000451 | | | |
| | Adjusted R-squared | 0.005897 | | | | Adjusted R-squared | -0.011094 | | | |
| **Monero** | C | -0.001898 | 0.002233 | -0.849897 | 0.3954 | C | 0.00361 | 0.003546 | 1.018177 | 0.3086 |
| | BITCOIN (-1) | 0.058657 | 0.067587 | 0.867875 | 0.3855 | BITCOIN (-1) | 0.158688 | 0.088111 | 1.801003 | 0.0717 |
| | R-squared | 0.033509 | | | | R-squared | 0.017881 | | | |
| | Adjusted R-squared | 0.02625 | | | | Adjusted R-squared | 0.007405 | | | |

## 5. CONCLUSIONS

The results of this study were expected to be in support of the idea that the two periods of Bitcoin due to asymmetry in prices and volatility to have a different effect on altcoins. The Bitcoin's leading position appears to have an influence on other cryptocurrencies; however, our findings indicate that periods we picked differ in how they affect altcoins. Dramatic changes in the price of the Bitcoin lead the other cryptocurrencies to be less responsive to the movements of the dominant. The most of our altcoins show a lesser reaction in the second period. We should remember that prices are extremely apart from each other and the altcoins simply cannot follow the Bitcoin's fluctuations. This suggests that the factors that have an impact on prices of the Bitcoin and altcoins are not the same. In the events of high volatility, the cryptocurrencies may be distinctive from each other the most. High rapid price change of the Bitcoin showed less spillover effect.

To conclude we assume the second period showed how different the cryptocurrencies are. The Bitcoin appears to be separated from the rest of cryptocurrencies by some factors that form this type of distinctive pricing. It may mean that diverged from each other the cryptocurrencies become more independent and are not exposed to the same factors of influence. This means that news or other more plausible causes that may change the prices of one cryptocurrency may not do the same with another.

To address the limitations and shortcomings of this work we should point out the imperfections of our model. We believe that the model can be improved with including more variables that truly play important role in price formations and volatility. With additional variables, the model should become more complex and precise which the current condition is not excelling to do so. Also, the more cryptocurrencies should be involved. Having an abundance of cryptocurrencies in the market it can be achieved. In addition, for the fact that cryptocurrency is a fairly new phenomenon and data cannot be extended for decades, in the future the longer periods should be considered. At the same time, future research should focus on how the market of cryptocurrencies correlates with the stock market. The further researchers may find interesting to pay more attention to a psychological part of this issue. As the behavioral finance is being one of the core directions for learning about the stock market.

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