A COMPARATIVE STUDY OF BITCOIN'S
RETURNS DYNAMICS

by

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LIST OF ABBREVIATIONS

ACF Autocorrelation Function

ADF Augmented Dickey-Fuller Test

ARCH Autoregressive Conditional Heteroskedasticity

BTC Bitcoin

CPI Consumer Price Index

DCC GARCH Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity

FnG "Fear and Greed" Index

OLS Ordinary Least Squares

PP test Phillips-Perron test

VAR Vector Autoregression

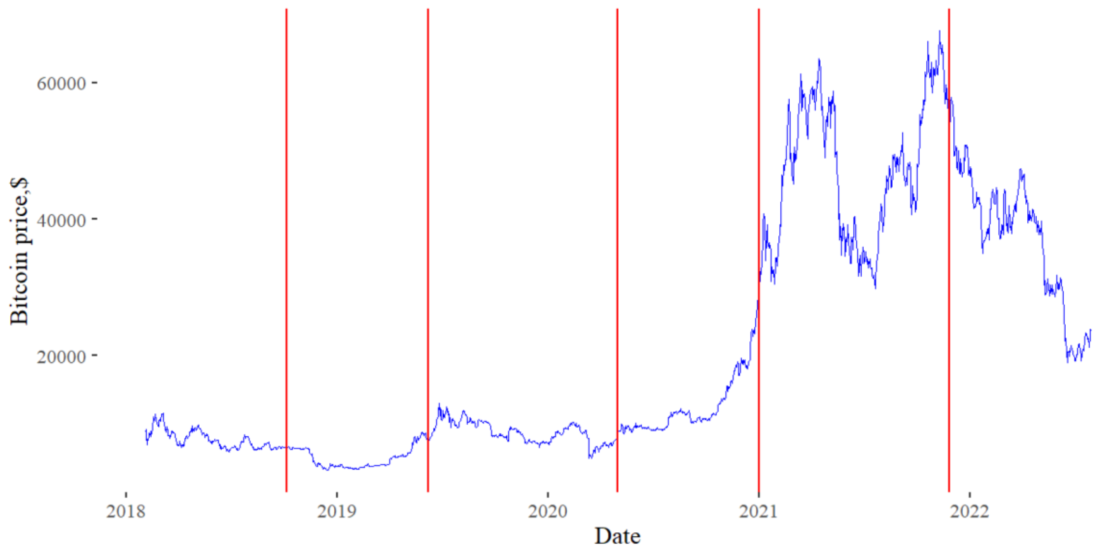
VIX Volatility Index

CHAPTER 1. INTRODUCTION

In recent times Bitcoin has attracted a lot of attention from financial institutions, governments, and research centers. The Bitcoin image changed from some funny stuff for geeks to an investment asset. Now we can say that it is adopted by the market as a financial instrument which requires a deeper investigation of its nature, behavior, and possible driving forces. A good starting point for this research is the studying of Bitcoin price history.

Bitcoin was revealed to the market by Satoshi Nakamoto in 2009 and its price was 0.00 USD at that time. In October 2010 its price reached the level of 0.10 USD and this period is known as a "first jump". Very few people knew about this asset and they were mostly tech and financial experts. In April 2011 the level of 1.00 USD was overcome and Bitcoin started its first three months bull rally with a peak value of 30.00 USD. This rally didn't last long and in November 2011 the price fell to the level of 2.00 USD. In April 2013 the crypto hit the level of 100.00 USD and continued to grow to reach 1 000.00 USD in November 2013. Then the price dropped again. At that time people started to ask themselves why the virtual asset could have real value. This issue remains debatable for now. Until 2017 the price was stable and only that year reached 1 000.00 USD for the second time in its history. Starting from 2017 we see the second bull run which lasted till the end of the year and the new maximum value of 19 000.00 USD was reached. The period from 2018 to October 2020 is characterized by the Bitcoin price which moved within the corridor without an evident trend. Starting from the end of October 2021 the third bull rally drew the Bitcoin price to the highest level at that time – 63 000.00 USD. That rally was associated with the shift of the sentiment toward Bitcoin among institutional investors and hedge funds. They started to promote purchasing Bitcoin instead of doubting its perspectives. The period from April 2021 to April 2022 can be described as a period of ups and downs. Starting from May 2022 the market follows a bearish trend (the Bitcoin price is falling). The Bitcoin price movements are depicted in the Figure 1.

Figure 1. Bitcoin price during 2018-2022 years in USD



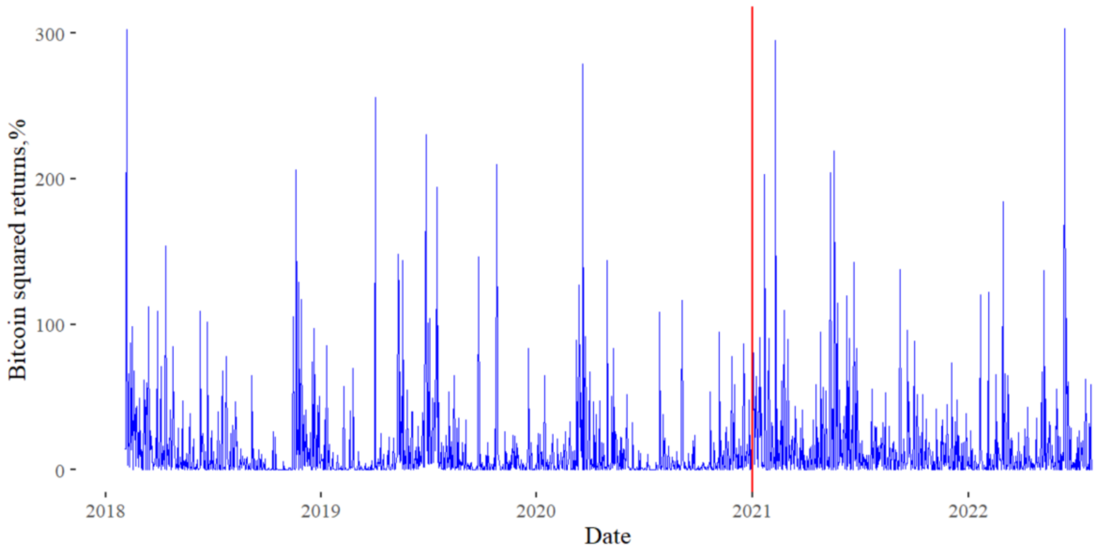
Note: the red vertical lines indicate the structural breaks in price
Source: https://www.blockchain.com/charts/market-price

Since most investors are interested not in the prices but returns, it is more reasonable to concentrate the research on the factors which influence those price changes (returns). Studying the returns is important because:

- higher returns mean that the price changes are greater;
- higher returns imply higher risks because the theory of efficient markets excludes the possibility of arbitrage opportunities (riskless profit);
- knowing the returns' driving forces will help to measure their effects and (knowing the nature of those drivers and factors which affect them) anticipate the periods with higher (lower) returns and higher (lower) risks. Also, it will help to choose the best moment to enter or leave the market.

We assume that the Bitcoin returns are associated with the change in the number of payments with Bitcoin, the number of unique addresses, the hash rate (total computational power of the blockchain), the "fear and greed" index, the Nasdaq Composite index and those changes are positively correlated. Also, we assume that the returns in the period from January 2021 to June 2022 were greater in absolute value than the returns in the period from February 2018 to January 2021 and it was caused by the changed effects of the variables mentioned above. Figure 2 depicts the squared Bitcoin returns and shows that it might be true.

Figure 2. Bitcoin squared returns in 2018-2022 years, %[1]



Note: red vertical line indicates a structural break in price in 01.01.2021

To confirm (or reject) our hypothesis we will split the whole period into two subperiods. The first subperiod lasts from 01.02.2018 to 31.12.2020. The first date is chosen because the "fear and greed" index is included in our model and its historical data are available only from 01.02.2018. The end of the subperiod is 31.12.2020 which is the date preceding the structural break of 01.01.2021. Also, this date stands for the start of the period of maximum Bitcoin prices. October 2020 is regarded as the month when institutional investors and hedge funds changed their sentiment toward the crypto market and started to promote purchasing the crypto instead of hesitating in it and we think that those tendencies came to power till the end of 2020. Also, we can notice that till the end of 2020 the price was quite stable but starting from 2021 we see a period of large ups and

[1] The negative returns in 12.03.2020 of - 46.4702 % was excluded from the graph to see the clearer picture.

downs. This is our motivation for choosing 01.01.2021 as a breaking point.

To indicate the difference in the effects of the explanatory variables between those subperiods we will use a dummy variable “Period” with 0 for the first (base) subperiod and 1 for the second subperiod. Each variable will be included in the model as the interaction term. Since the data are time series data, this requires checking all variables for stationarity to avoid “spurious” regressions and results.

CHAPTER 2. LITERATURE REVIEW

In this section, we will review the following issues: what is the nature of cryptocurrency; what is the difference between two blockchain consensus models; what factors can potentially affect its price.

Bitcoin is a blockchain technology and can be described as a sequence of transactions connected to a chain. Each transaction forms a block which in turn is attached to the chain and can't be removed or changed. If there is an error, a new block has to be created to cancel the previous wrong one. Each transaction must be approved by all the members of the blockchain system. To facilitate the transactions the mechanism of smart contracts can be used. This is the set of rules which are applied to all or particular transactions automatically. Each transaction is available for all members and there is no need to insert the data in the system many times, just once.

In 2008 Satoshi Nakamoto published the most influential paper in the cryptocurrency field – "Bitcoin: a peer-to-peer electronic cash system" (Satoshi Nakamoto, 2008). In this paper he described the general view of the financial system without the need for any third party like a bank to confirm the transaction. "What is needed is an electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party" (Satoshi Nakamoto, 2008).

Each transaction forms a block that is added to the blockchain and can be verified by every member of the system. To prevent double spending each member has to confirm the transaction. Two types of "consensus mechanism" can be used: "proof of work" and "proof of stake".

In the "proof of work" mechanism validators solve some math puzzles to validate the block, add it to the blockchain and get a reward in a cryptocurrency (bitcoin uses this mechanism). If they failed, the cost of it is lost time and electricity.

In the "proof of stake" consensus mechanism a pool of "validators" authorizes each block contributing a "stake" of cryptocurrency and, if the transaction is proven to be correct, gets a reward. If a wrong transaction is added to the blockchain, validators are punished by reducing their stake in cryptocurrency.

As for the factors which influence cryptocurrency prices, the first attempts to investigate this phenomenon were made a couple of years after the Bitcoin emergence. The researchers tried to connect the Bitcoin price with different macroeconomic indicators and commodities. Later the specific to Bitcoin factors (supply and demand, attractiveness, computing power, momentum) were included in the models.

Ladislav Kristoufek found out that the Bitcoin price is driven mostly by speculative demand. The fundamental factors (usage in trade, supply) play role in the long run (Kristoufek, 2015). Also, he pointed out that the price of Bitcoin is heavily influenced by the investors' attention and the cryptocurrency can't be regarded as a safe haven due to its high volatility (Kristoufek, 2015).

Pavel Ciaian et al. contributed to the research on the factors that determine the BTC price. Their findings state that the key price factors are supply and demand for BTC, and investment attractiveness (views on Wikipedia) is significant only in the short run. Macroeconomic variables (stock indices, commodity prices) are significant in the short run (Ciaian et al., 2016).

Donier and Bouchaud investigated the Bitcoin market crash in 2013 and claimed that most market crashes took place when there was not any significant news on the market. So, they say that large price movements occur due to the exogenous price cycle, not because of some news (Donier and Bouchaud, 2015).

Siddharth M. Bhambhwani et al. found empirical evidence that the aggregate computing power and the number of users can affect the cryptocurrency price because these factors reflect the trustworthiness of the system and transaction benefits (Siddharth M. Bhambhwani et al., 2019). Many experts claim that cryptocurrencies do not have their own intrinsic value (like gold or other commodities) and because of this very hard to establish the estimation methodology. Siddharth M. Bhambhwani et al. (2019) state that cryptocurrencies have intrinsic value which takes its roots from the blockchain's hash rate (computing power) and the users' number (market adoption).

Baur et al. (2018) relied on the hypothesis opposite of Siddharth M. Bhambhwani et al. They think that BTC doesn't have an intrinsic value. In analyzing price factors they concluded that Bitcoin is uncorrelated with stocks, bonds, and commodities and behaves as a speculative asset, not a transaction mean (Baur et al., 2018).

Further research by the same authors investigated only the relationship between gold and BTC. The results were not different from the previous research and revealed that the correlation between these two assets is almost absent (Baur et al., 2021).

Liu and Tsyvinski (2018) confirmed the findings of Baur et al. They found that the risk-return trade-off is distinct from stocks, currencies, and gold. Cryptocurrencies do not have close relations with macroeconomic variables or the returns of currencies and commodities. Instead, the cryptocurrencies price is driven by the investors' attention and momentum effect (Liu and Tsyvinski, 2018).

The research of Bianchi (2020) stays in line with the previous two and claims that there is no significant relationship between returns on cryptocurrencies and other traditional asset classes (stocks, bonds, precious metals). Macroeconomic factors (inflation, Fed rate) do not affect the trading activity of crypto. It is driven mostly by the investors' sentiment (Bianchi, 2018).

Sana Guizani et al. made a research of the factors which can cause Bitcoin volatility. The most significant factor appeared to be the demand from the investors. The supply of newly issued Bitcoins is not significant in the short and long run, because it is predetermined to the 21 mln coins. Macroeconomic and financial determinants didn't prove their significance in the short and long run. Also, the mining difficulty is significant in the short run but loses its significance in the long run (Sana Guizani et al., 2019).

The research on the Bitcoin price volatility made by Xu et al. (2021) revealed that Bitcoin's own factors (transaction and speculation demand) have the greatest impact on its volatility. Gold price, US dollar supply, and S&P 500 also contribute to the volatility, but on the later lags. The supply factor proved to be insignificant and doesn't affect cryptocurrency volatility (Xu et al., 2021).

One of the most relevant papers to our research was written by Zayn Khamisa in April 2019. He studied the factors which could influence the returns of different cryptocurrencies and used OLS regressions to assess the effects of independent variables. The same method we will use in our thesis. He found out that the exchange volume is the major driving force of the returns, the transaction volume has a negative effect on returns in the long run, MSCI World index and the oil price have no relationship to cryptocurrency performance.

In our research we will use the set of variables similar to the variables investigated in the papers listed above. The OLS regressions are used to analyze the relation between variables. Also, we include "fear and greed" index as a new variable that is the composite measure of the investors' sentiment toward the cryptocurrencies. The main goal of our research is to identify the factors which drive the returns and assess how their effect changed in the second period relative to the first. To do this we include the dummy variable for a period and use the interaction terms. The analyzed data frame is also wider because we can analyze longer Bitcoin price history. These are the main aspects which differ our research from the works mentioned above.

CHAPTER 3. METHODOLOGY

This thesis aims to identify the factors which affect the changes in the Bitcoin price during two time periods: 01.02.2018 - 31.12.2020 and 01.01.2021 – 31.07.2022. These two periods are chosen because of their very different Bitcoin price behavior. That can be caused by the different effects of the factors (specific to Bitcoin and others common to stock markets). Being aware of such factors and their potential influence can help to identify the right moment to enter or leave the market.

As we know, Bitcoin's price behavior has a low correlation with the financial markets, macroeconomic variables, and commodities (oil, gold, etc.), and is driven by the factors which are specific to cryptocurrencies. The low correlation with the stock market will be checked. Among these factors are:

- supply of Bitcoin;
- demand for Bitcoin;
- momentum;
- fear and greed index;
- hash rate (network computing power) and the difficulty of mining.

Each variable requires a clear description and identification of the possible effect on the explained variable.

Bitcoin's supply is determined by the algorithm with the maximum amount set to 21 mln coins. New coins are generated approximately every 10 minutes and their mining is independent of price. The supply is decreasing geometrically with 50 % every 210 000 blocks mined. So, the supply is constantly approaching 21 mln but never riches it. The proxy for the supply is the total number of mined Bitcoins. We can't use the total market capitalization in USD because Bitcoin's price is very volatile and it may seem that the supply is also volatile which is not true.

The most important factor for the cryptocurrency price and its returns is the demand. For our thesis we will not distinguish the demand for transactional and speculative and will take it as an aggregate variable. The question is what can serve as a proxy for demand?

The first variable which depicts the demand for Bitcoin is the number of transactions per day. The Bitcoin network allows a single transaction to include many payments. This process is called "batching" and is a more efficient way to send payments to multiple recipients. The average number of payments in a transaction is not constant and can vary substantially. So, it is more reliable to use the number of payments per day for our research.

The second factor which influences the demand is the number of users. For our thesis, the number of unique addresses will be used.

The 3rd variable is the "fear and greed" index. It is a composite index that describes the investors' attitude towards the cryptocurrency market. The scale varies from 1 to 100 and the lower the index the more insecure investors are feeling. This variable incorporates the following factors:

- momentum and volume. Very high trade volume relative to the basis can indicate that the market is too enthusiastic about Bitcoin's perspectives;
- social media sentiment analysis is assessing the sentiment type and volume at a certain time concerning the historical norms;
- Bitcoin's dominance;
- Google Trends and the number of queries relevant to the cryptocurrencies.

The fourth factor is the hash rate or the network computing power. Hash rate measures the amount of computing power contributed to the network through mining. Mining is a process of performing very complex mathematical computations to verify the transactions which are grouped in blocks. If the block is verified, the miners receive a reward in a form of Bitcoin. A higher hash rate is positive for the network because miners' chances to find and verify the next block are increasing. Also, high hash rate signals that the network is healthy, it is almost impossible to hack it and change the past transactions which, in turn, leads to higher Bitcoin values.

To be consistent and double-check the hypothesis that the Bitcoin price is uncorrelated to financial (derivative) markets we will include the sixth variable which can potentially be related to the cryptocurrency. How to choose this variable? The first way of thinking about cryptocurrencies as a safe haven, a tool for reducing inflation losses. If it is the case, the crypto has to be negatively correlated with the inflation and interest rate. Recent researches proved that this is not true. So, Fed rate, CPI, and other macroeconomic variables can't be included in our model. The second approach to Bitcoin as a risky, highly volatile asset with high rewards. The investors which are not satisfied with low returns and relatively high risks choose to invest in crypto with the hope to gain very high profit despite the high risk. The plausible candidate for such a variable is a NASDAQ Composite Index since the Bitcoin can be treated by the market as a risky tech stock. We assume the positive correlation between Bitcoin and NASDAQ Composite index.

Also, we will add to the model VIX index which indicates the investors' sentiment about the stock market: whether they are optimistic or pessimistic about future prospects. We assume that VIX is negatively correlated with the Bitcoin's price and returns.

For our research we will use time-series analysis. The model is described by equation (1):

$$\Delta \mathrm{Pr} = f(\Delta \mathrm{D}_{BP},\ \Delta \mathrm{D}_{UA}, \Delta \mathrm{HR}, \Delta \mathrm{FG}, \Delta \mathrm{NAS}, \Delta \mathrm{VIX})^{2} \quad (1)$$

where:

$\Delta \mathrm{Pr}$ – change of Bitcoin price (returns), %;

$\Delta \mathrm{D}_{BP}$ - change of the total number of confirmed payments per day, %;

$\Delta \mathrm{D}_{UA}$ - change of the total number of unique addresses used on the blockchain, %;

$\Delta \mathrm{HR}$ – change of the total hash rate, %;

$\Delta \mathrm{FG}$ – change of the "fear and greed" index, %;

$\Delta \mathrm{NAS}$ - change of the NASDAQ Composite Index, %;

$\Delta \mathrm{VIX}$ - change of the volatility index, %

[2] Running a model with "fear and greed" index and VIX index in levels resulted in the insignificance of the first variable whereas it was significant in the percentage changes. VIX index was insignificant in both cases. To be consistent we included both variables in the percentage changes

The aim of these thesis is to test two hypotheses using the variables listed above. **Hypotheses 1:** the greater change in the Bitcoin prices in the second period is associated with the greater effect of the change in the independent variables. **Hypothesis 2:** the change in Bitcoin prices is associated only with the factors which are specific to crypto market, stock returns are uncorrelated with the Bitcoin returns.

The first step in the time-series analysis is checking the data for stationarity. The concept of stationarity implies that the mean and variance of the variable is constant over time. It is done by plotting the data and performing some formal statistical tests. These tests are cold the unit root tests. For our thesis we will use Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test. Both tests share the same null hypothesis that the data are not stationary. The alternative hypothesis states that the data are stationary. Performing these tests, we have to look on the p-value and if it is less than 0.05 we can reject H_0 assuming that our time-series is stationary.

If it turns out that all our variables of interest are stationary, we can use simple ordinary least squares (OLS) regressions or vector autoregressive (VAR) model. Since our variables are all the percentage changes, we assume that they are stationary. So, our main method is chosen the OLS regressions. To distinguish one period from another we use the dummy variable for a subperiod ("0" for the first and "1" for the second) and the interaction terms.

$$\Delta\mathrm{Pr} = \mathrm{P} * \Delta\mathrm{D}_{BP} + \mathrm{P} * \Delta\mathrm{D}_{UA} + \mathrm{P} * \Delta\mathrm{HR} + \mathrm{P} * \Delta\mathrm{FG} + \mathrm{P} * \Delta\mathrm{NAS} + \mathrm{P} * \Delta\mathrm{VIX} \qquad (2)$$

The coefficients of the interaction terms (if they are significant) tell us how the effect of the changes in the independent variables in the second period differ from that effects in the first period (provided that they are statistically significant). These results help us to accept or reject the hypotheses 1. To accept or reject the hypothesis 2 (the Bitcoin returns are uncorrelated with the stock returns) we have to look at the significance of beta coefficient of NASDAQ Composite index. If it is significant and is not zero we reject H_0 and can say that the Bitcoin returns are correlated with the stock returns.

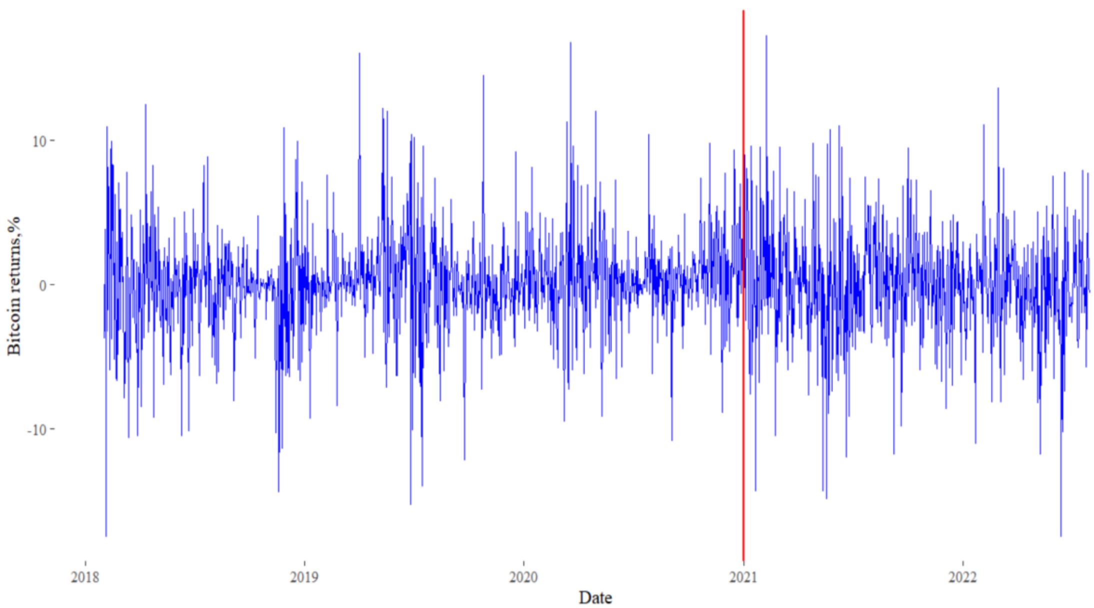
To investigate the conditional correlation between the change of the BTC price and the changes in the independent variables we will use DCC GARCH approach. This model allows us to get the correlation coefficients which varies over time. Using those approach requires checking the variables for the stationarity, the presence of the volatility clustering and the ARCH effect.

To verify the strength of our model we will conduct several tests: Durbin-Watson for the autocorrelation of residuals, Breusch-Pagan test for heteroskedasticity, and Shapiro-Wilk test for the normality of residuals. In the presence of heteroskedasticity in the residuals, we will rerun our regression with robust standard errors. Also, we will check that the beta coefficients are not zero and differ from each other performing the F-tests.

CHAPTER 4. DATA

Our analysis is aimed to investigate the factors which caused the change in Bitcoin's prices in the period 01.01.2021 – 01.07.2022 relative to the period 01.02.2018 – 31.12.2020. To explain these changes the daily Bitcoin's returns are chosen as a dependent variable. The graph of the daily returns is presented in Figure 3.

Figure 3. Bitcoin returns in 2018-2022 years, %[3]



Note: red vertical line indicates a structural break in price in 01.01.2021

The daily Bitcoin prices are taken from https://www.blockchain.com/charts/market-price as a consolidation of prices from the major crypto exchanges. The daily returns are calculated using the formula $r_t = 100 \times [\log(P_t) - \log(P_{t-1})]$. The descriptive statistics of the daily returns and other variables are presented in Appendix A. The mean daily return in the second period with the level

[3] The negative returns in 12.03.2020 of - 46.4702 % was excluded from the graph to see the clearer picture.

of -0.039 % shows that in the second period the prices were mostly falling. The deviation from the mean in the second period is higher.

As the explanatory variables the following factors were taken: the daily total number of payments with Bitcoin, the daily total number of unique addresses which took part in Bitcoin transactions, the daily total hash rate (computing power) of the blockchain network, the "fear and greed" index, NASDAQ Composite index, and VIX index. All variables are taken as a percentage change.

The daily total number of payments per day is taken from https://www.blockchain.com/charts/n-payments. We chose payments, not transactions because each transaction can include a different number of payments, so the number of payments is a more accurate indicator of the blockchain activity. This variable is chosen as a proxy for the demand for Bitcoin. The mean value in the first period indicates steady growth whereas in the second period we see a decrease in payments. The standard deviation is quite high (11.4663 %) and tells us that the variable is volatile.

The daily total number of unique addresses is taken from https://www.blockchain.com/charts/n-unique-addresses and it is another indicator of the blockchain activity. The variable is chosen as another proxy for the chain activity and demonstrates a constantly growing trend.

The daily total hash rate measures the amount of computing power contributed to the network through mining and is assumingly positively correlated with the returns. The data are taken from https://www.blockchain.com/charts/hash-rate. Its behavior is similar to the previous variable.

The "fear and greed" index describes the market sentiment (optimistic or pessimistic) over cryptocurrencies. The data are taken from https://alternative.me/crypto/fear-and-greed-index/ and range from 1 for the most pessimistic mood to 100 for the most optimistic. The index has the greatest minimum and maximum values and is very volatile.

NASDAQ Composite index was taken as a variable strictly related to the tech sector and assumingly with a positive correlation with Bitcoin. Meaning, when the market is bullish towards the tech sector the Bitcoin price also has to rise. The daily data are taken from https://cbonds.ua/indexes/264/.

VIX index depicts the market sentiment over prospects. High VIX is associated with high uncertainty and risk and we assume that it is negatively correlated with the Bitcoin price. The data were taken from https://cbonds.ua/indexes/1285/ daily.

Also, one dummy variable is introduced to the dataset to distinguish the first period from the second one.

The correlation table in Appendix B shows that the change in the Bitcoin price is correlated with the change in the "fear and greed" index, the change in the NASDAQ Composite index, and the change in the VIX index. So, we suspect these variables to be significant in the following OLS regressions. The correlation between the change in the "fear and greed" index and the change in Bitcoin price changed its sign from positive in the first subperiod to negative in the second one. It tells us about the changed effect of that variable in the second period. The correlation between the change in the NASDAQ Composite index, the change in the VIX index, and the change in Bitcoin price didn't change its sign in both subperiods but the magnitude is greater in the second subperiod. So, we assume that the changed behavior of Bitcoin price in the second subperiod can be caused by the alternated effect of the change in the "fear and greed" index and the greater influence of the change in the NASDAQ Composite and VIX indexes.

CHAPTER 5. ESTIMATION RESULTS

5.1. Unit root test

Unit root test is the statistical approach to testing the mean, variance, and covariance of a time series on stationarity using an autoregressive model. The test is necessary because for the OLS regressions we have to take only stationary data (I(0) order of integration). Using nonstationary data results in "spurious" regressions and unreliable results.

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are performed for each variable in levels and differences. Both tests have the null hypothesis that the data are nonstationary and if the p-value is less than 0.05 the null hypothesis is rejected. The tests' results are presented in Table 1.

Table 1. Unit root tests

	ADF test			PP test		
Variable	t-statistics	p-value	Result	t-statistics	p-value	Result
Variables in levels						
returns_bts	-14.41	0.01	S	-1856.40	0.01	S
d_n_payments	-16.034	0.01	S	-1262.70	0.01	S
d_n_addresses	-15.336	0.01	S	-520.12	0.01	S
d_hash_rate	-13.018	0.01	S	-381.19	0.01	S
d_fear_greed_index	-16.701	0.01	S	-1756.30	0.01	S
d_NASDAQ	-15.935	0.01	S	-1425.20	0.01	S
d_VIX_index	-13.903	0.01	S	-1195.60	0.01	S
Differenced variables						
d_returns_bts	-23.605	0.01	S	-1851.40	0.01	S
dd_n_payments	-41.742	0.01	S	-1771.00	0.01	S
dd_n_addresses	-24.743	0.01	S	-1012.00	0.01	S
dd_hash_rate	-19.526	0.01	S	-1204.30	0.01	S
dd_fear_greed_index	-27.648	0.01	S	-2074.40	0.01	S
dd_NASDAQ	-24.987	0.01	S	-1952.00	0.01	S
dd_VIX_index	-23.078	0.01	S	-1782.70	0.01	S

Note: NS – not stationary variable, S – stationary variable

All variables are stationary in levels and differences. Since our research is aimed to investigate the factors which affect the change in Bitcoin's prices and all the variables are integrated of order I(0) linear regression is chosen as the tool for further research.

5.2. Models' estimation and interpretation

The ordinary least squares method was chosen because all variables are stationary, the method gives the opportunity to easily interpret the coefficients and (which is the most important thing) allows us to compare the factors which affected the returns in two subperiods incorporating the dummy variable to the subperiods. Our strategy is the following:

- estimating the OLS for the whole period;
- estimating the OLS for the first subperiod (01.02.2018 – 31.12.2020);
- estimating OLS for the second subperiod (01.01.2021 – 31.07.2022);
- including the dummy variable "Period" with the value 0 for the first subperiod and 1 for the second to the first regression to see the difference between independent variables' effects;
- interpreting the results for each regression.

The results are presented in Table 2. The first thing which catches our sight is that only two variables are significant for the change in Bitcoin price – the change of the "fear and greed" index and the change of the NASDAQ Composite index. All the other variables are insignificant.

Also, we can notice that in the first subperiod the percentage change of the FnG index positively affected the Bitcoin returns (each additional percent to the positive percentage change of the FnG index resulted in an additional 0.0164 % to the Bitcoin returns). Meaning that the difference in prices in a period [t; t-1] was increasing in response to the increase in the difference of FnG index in the same period. Whereas in the second period this factor had the same significance level but completely changed its sign from positive to negative.

Table 2. OLS regressions

Variables	OLS (full period)	OLS (01.02.2018-31.12.2020)	OLS (01.01.2021-31.07.2022)	OLS with dummy (full period)
	Estimate	Estimate	Estimate	Estimate
Intercept	0.0217	0.0758	-0.0701	0.0762
Period 1				-0.1446
d_n_paym	0.0044	0.0091	0.0000	0.0090
d_n_address	0.0085	0.0092	0.0096	0.0092
d_hash_rate	0.0406	0.0368	0.0498	0.0370
d_fng_index	0.0054	0.0164**	-0.0156*	0.0163**
d_nasdaq	0.6707***	0.5530***	0.9167***	0.5530***
d_VIX_index	0.0080	0.0245	-0.0111	0.0245
P_1:d_n_paym				-0.0087
P_1:d_n_address				0.0003
P_1:d_hash_rate				0.0136
P_1:d_fng_index				-0.0320***
P_1:d_nasdaq				0.3638*
P_1:d_VIX_index				-0.0357
Observations	1642	1066	576	1642
R^2	0.0687	0.0501	0.1355	0.0816

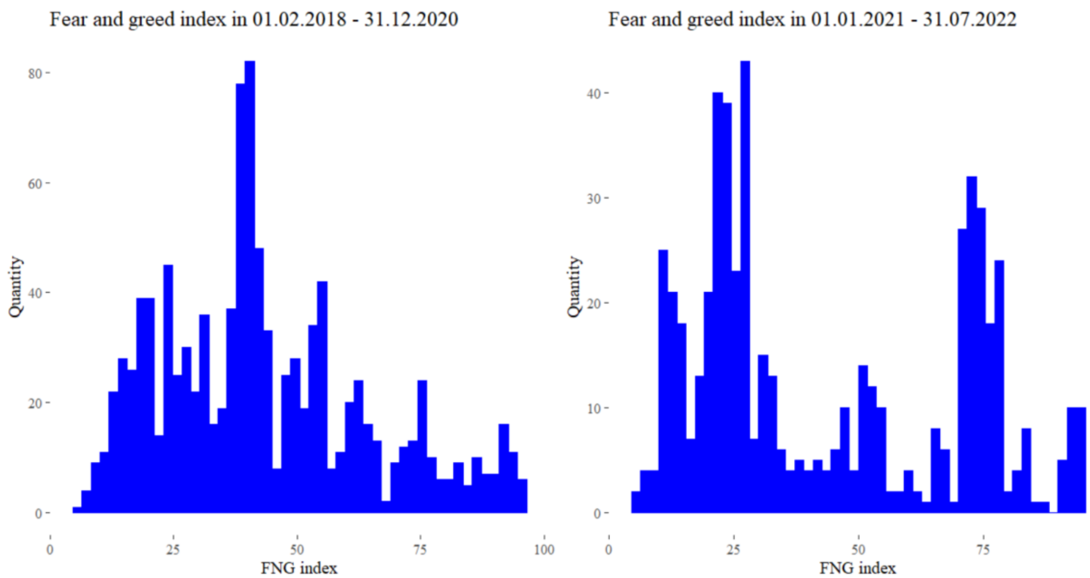
Note: *p<0.1, **p<0.05, ***p<0.01

Meaning each additional percent to the positive percentage change of the FnG index reduced the Bitcoin returns on 0.0156 % (the difference in prices in period [t; t-1] was decreasing in response to the increase in difference of the FnG index in the same period).

The effect of the change of the NASDAQ index on the Bitcoin returns was positive and significant in both subperiods with the increased effect in the second one.

The question is why the sign of the effect of the percentage change of the FnG index changed in the second period? To answer this question, we plotted the histograms of the FnG index for the two subperiods to see what values were the most common. They are presented in the Figure 4.

Figure 4. "Fear and greed" index in 2018-2022 years

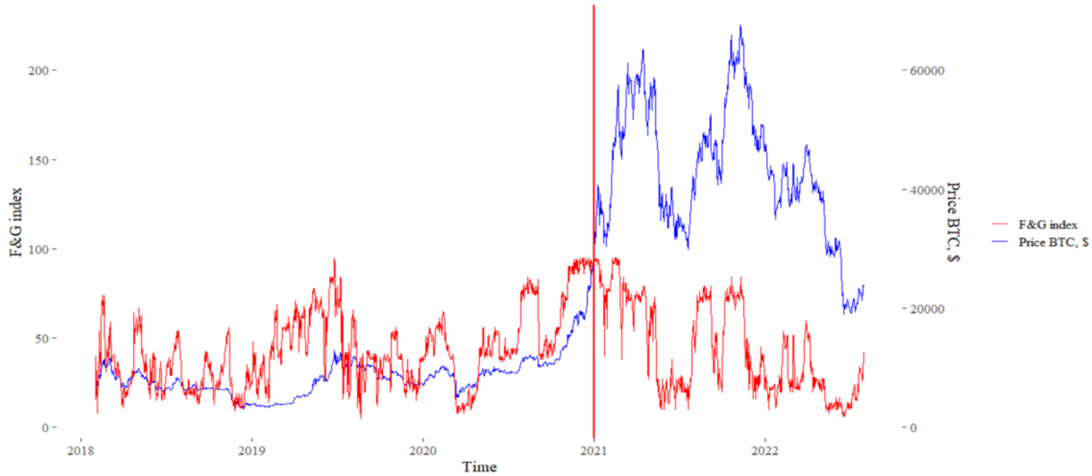


Source: https://alternative.me/crypto/fear-and-greed-index/

It is clearly seen that during the 1st subperiod the values of the FnG index were mostly less than 50, meaning that the market was skeptical about the Bitcoin perspectives. Whereas during the 2nd subperiod the index fluctuated between the extreme values from the extreme optimism (FnG index - 75) to the extreme pessimism (FnG index – 25). So, we assume that the alternation of the sign of the effect of the change in the FnG index on the change in Bitcoin price in the second subperiod was caused by the fact that during the 1st subperiod the value of the FnG index was mostly below 50, the market was quite skeptical about the Bitcoin perspectives and there was a lot of space for the further increase in the Bitcoin returns. The 2nd subperiod started from the level of the FnG index which was close to the maximum and remained higher than 50 till the second half of 2021 (Figure 5). So, there was not too much space for the increase in the Bitcoin returns (the market was too optimistic). Each additional percentage change in the index didn't meet the proportional increase in the returns.

To see the comovement of the Bitcoin prices and the FnG index we constructed a plot for the whole period (Figure 5).

Figure 5. The comovement of the BTC price and “fear and greed” index in 2018-2022



Note: red vertical line indicates a structural break in price in 01.01.2021
Source: https://alternative.me/crypto/fear-and-greed-index/,
https://www.blockchain.com/charts/market-price

The interaction term “Period1 * FnG index” tells us that:

- the positive changes in the percentage change of the FnG index have the effect on the Bitcoin returns which is on 0.0320 % less in the 2nd subperiod relative to the 1st one;
- the negative changes in the percentage change of the FnG index have the effect on the Bitcoin returns which is on 0.0320 % higher in the 2nd subperiod relative to the 1st one;
- the Bitcoin price was more sensitive to the negative shocks in the FnG index during the 2nd subperiod.

So, knowing the increased sensitivity of the Bitcoin returns to the negative shocks in the FnG index in the second subperiod we calculated the sum of the positive and negative percentage changes of the FnG index for both subperiods. In the first subperiod positive changes outweighed the negative ones (“7377” vs “-7189”) whereas in the second one the negative changes were prevailing (“-4150” vs “4071”). So, we assume that the increased sensitivity of the Bitcoin returns to the negative shocks of the change in the

FnG index was one of the factors contributing to the increased changes in the Bitcoin prices in the second subperiod.

The effect of the percentage change in the NASDAQ Composite index was significant during both subperiods, it didn't change its sign (being always positive). The magnitude of its effect on the change in the Bitcoin prices increased in the second subperiod relative to the first one on 0.3638 %.

Due to the potential issues with the heteroskedasticity the effects of all variables will be reestimated through the running OLS regressions with the robust standard errors.

5.3. Conditional correlation

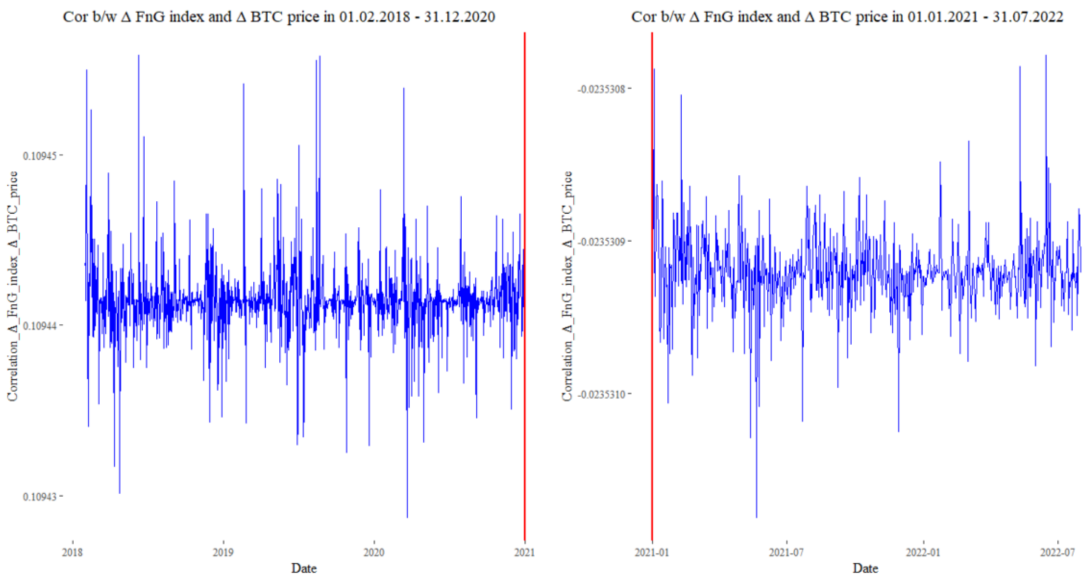
Using OLS models for assessing the factors which influence the change in Bitcoin prices doesn't consider the conditional correlation between the variables over time. On the Figure 3 we see that the changes of the Bitcoin prices were not constant over time and the volatility clustering is present. The most appropriate instrument to deal with such an issue is the GARCH models. There are plenty of univariate GARCH models, but we want to investigate the changed correlation between the variables over time. To do this we will use DCC GARCH model (dynamic conditional correlation generalized autoregressive conditional heteroskedasticity model). It is a multivariate GARCH model which allows to investigate and plot the changed correlation between two or more variables.

The first step is to check all the variables for stationarity, since GARCH models works only with the stationary data (all variables are stationary). The second step is to check the variables for the volatility clustering and the presence of the ARCH effect. The presence of the volatility clustering was assessed visually and all the variables have this property. The presence of the ARCH effect was assessed through preforming the ARCH test (null hypothesis – ARCH effect is absent). All the variables have the ARCH effect.

We performed DCC GARCH model for the Bitcoin returns in pair with each variable. Only the correlation between the changes of the FnG index, the NASDAQ

Composite index and the Bitcoin price are worth noticing. The conditional correlation between the change of the FnG index and the Bitcoin price displayed on the Figure 6.

Figure 6. The conditional correlation between Δ FnG index and Δ BTC price in 2018-2022 years (DCC GARCH model)

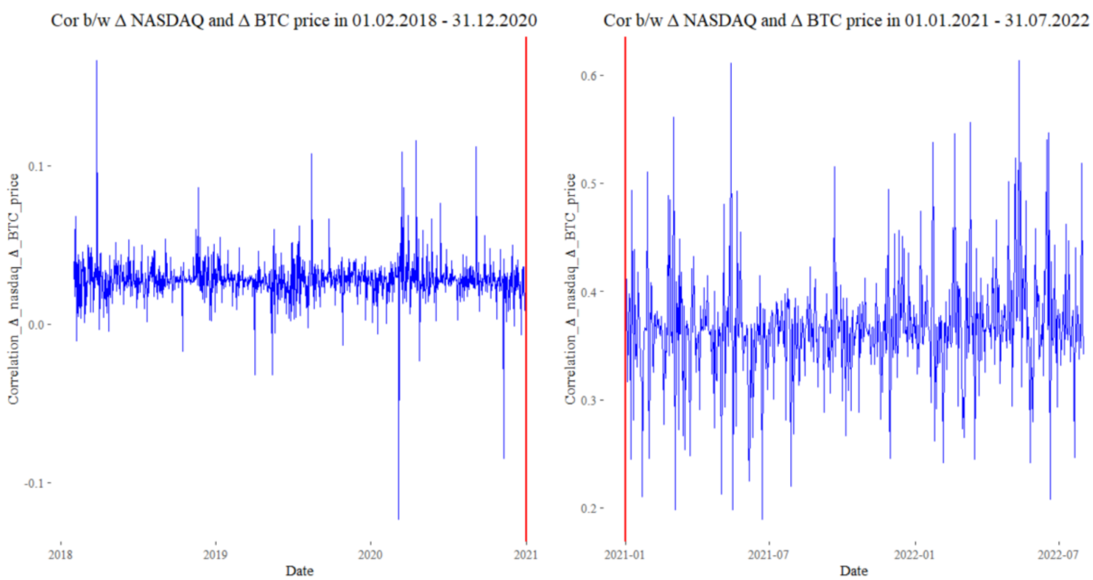


Note: red vertical line indicates a structural break in price in 01.01.2021

From the Figure 6 we see that the disturbances of the correlation are present during both subperiods, during the first subperiod the correlation between the ΔFnG index and ΔBTC price was positive, during the second subperiod it changed its sign to negative (the nature of this alternation was explained in the chapter 5.3). However, the magnitude of the correlation disturbances was very small (0.00002 for the 1st subperiod, 0.0000002 for the 2nd) and we state that those disturbances didn't bring the additional volatility to the ΔBTC price. Also, we have to notice moderate correlation in the 1st subperiod and low correlation in the 2nd subperiod.

The next variable of interest is the correlation between the changes in the NASDAQ Composite index and the Bitcoin prices. The Figure 7 displays those relations for each subperiod.

Figure 7. The conditional correlation between Δ NASDAQ index and Δ BTC price in 2018-2022 years (DCC GARCH model)



Note: red vertical line indicates a structural break in price in 01.01.2021

The graph of the conditional correlation between the ΔNASDAQ index and ΔBTC price during the 1st subperiod revealed the small fluctuations around the mean value of approximately 0.03 (quite a weak correlation). In the 2nd subperiod the correlation mean value increased significantly to the level of approximately 0.35. Moreover, the magnitude of the fluctuations increased also (min value – 0.20, max value – 0.60). It is evident that during the 2nd subperiod the ΔBTC price responded significantly to the ΔNASDAQ index and those responses were far greater than in the 1st subperiod. So, we state the increased conditional correlation between these variables added significantly to the increased changes in the Bitcoin price in the 2nd subperiod.

5.4. Post-estimation tests

Post-estimation tests are necessary to prove the models' results' reliability. For our models we have to check 3 issues:

- the normality of errors distribution;
- the heteroskedasticity (the variance is constant or not, tells us whether the coefficients of our model are biased or not);
- the errors autocorrelation (tells us whether some information is left in the residuals).

To check the normality, we will use the Shapiro-Wilk test with the null hypothesis that the residuals are normally distributed. If the p-value is less than 0.05, we reject the null hypothesis and claim that the residuals are not normally distributed. Also, we will plot the residuals for each model. The residuals graph will be provided only for the model with a dummy variable (the model of our interest).

To check the heteroskedasticity we will use the Breusch-Pagan test with the null hypothesis of no heteroskedasticity in the model (the variance is constant). If the p-value is less than 0.05, we state that there is heteroskedasticity in the model (the variance is not constant). To eliminate that effect from the model and get unbiased coefficients we will rerun each model with robust standard errors.

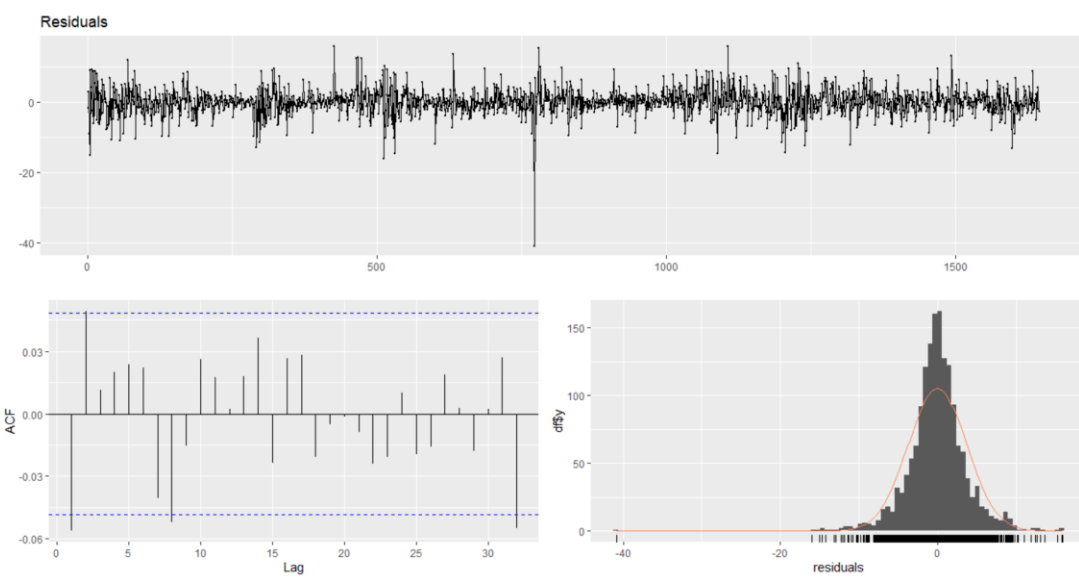
Table 3. Post-estimation tests

Test	OLS (full period)	OLS (01.02.2018-31.12.2020)	OLS (01.01.2021-31.07.2022)	OLS with dummy (full period)
Shapiro-Wilk (p-value)	0.00	0.00	0.00	0.00
Normality	-	-	-	-
Breusch-Pagan (p-value)	0.00	0.00	0.00	0.00
Heteroskedasticity	+	+	+	+
Durbin-Watson (DW test value)	2.12	2.17	1.98	2.11
Autocorrelation	-	-	-	-

To check the residuals' autocorrelation, we will use the Durbin-Watson test. Its values range from 0 to 4. The test's value from 0 to 2 indicates positive autocorrelation and the range from 2 to 4 reflects negative autocorrelation. The rule of thumb tells the following: the test's result from 1.5 to 2.5 indicates no autocorrelation in the model. Also, we will perform the ACF tests for each model and present the results only for the model with the dummy variable.

Shapiro-Wilk test tells us that the residuals are not normally distributed for all the models. Our main model of the interest is the last model with a dummy variable so we made a residuals plot for that model (Figure 8).

Figure 8. OLS with the dummy. Residuals plot, ACF plot, and residuals' variance



The ACF plot of the residuals tells us that there is no autocorrelation (all values are within the blue dotted lines). The histogram of the residuals is close to a bell-shaped form so, we can assume that the residuals' distribution is close to normal.

The Breusch-Pagan test also failed for each model – there is heteroskedasticity in the models (the variance is not constant). The residual's graph tells us the same. It means that our estimates could be insignificant if we estimate the regression with robust standard errors. The regressions' results with the robust standard errors are presented in Table 4.

Table 4. OLS regressions with the robust standard errors

Variables	OLS robust (full period)	OLS robust (01.02.2018-31.12.2020)	OLS robust (01.01.2021-31.07.2022)	OLS robust with dummy (full period)
	Estimate	Estimate	Estimate	Estimate
Intercept	0.0217	0.0758	-0.0701	0.0762
Period 1				-0.1446
d_n_paym	0.0044	0.0091	0.0000	0.0090
d_n_address	0.0085	0.0092	0.0096	0.0092
d_hash_rate	0.0406	0.0368	0.0498	0.0370
d_fng_index	0.0054	0.0163***	-0.0156**	0.0163***
d_nasdaq	0.6707***	0.5530***	0.9167***	0.5530***
d_VIX_index	0.0080	0.0245	-0.0111	0.0245
P_1:d_n_paym				-0.0087
P_1:d_n_address				0.0002
P_1:d_hash_rate				0.0136
P_1:d_fng_index				-0.0320***
P_1:d_nasdaq				0.3638
P_1:d_VIX_index				-0.0357
Observations	1642	1066	576	1642
R^2	0.0687	0.0501	0.1355	0.0816

Note: *p<0.1, **p<0.05, ***p<0.01

The robust OLS regression with a dummy variable shows us that ΔFnG index and ΔNASDAQ do not lose its significance. The interaction term "Period1 * FnG index" is also significant. The interaction term "Period1 * NASDAQ" lost its significance. Its 95% confidence interval lies within -0.133 and 0.86 so we can't reject the null hypothesis that the coefficient of this term equals to zero. It means that the effect of the change of the NASDAQ index on the change in BTC price in the 2nd subperiod varies from its effect in the 1st period but this change is not significant. But this conclusion can be made only assuming that the variance of those variables is constant. As we saw earlier it is not the case and we proved that BTC priced reacted stronger to the changes in NASDAQ in the 2nd subperiod due to the changing conditional correlation. So, we consider the interaction term "Period1 * NASDAQ" as being significant.

Durbin-Watson statistics are less than 2.5 for each model so we can assume that there is no autocorrelation in the residuals The ACF plot in Figure 8 for the model with a dummy tells us the same.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

The goal of our research was to identify the factors which caused greater changes in the Bitcoin prices in the period from 01.01.2021 to 31.07.2022 in comparison with the period from 01.02.2018 to 31.12.2020. Among all the variables only two of them appeared to be significant: the change in the "fear and greed" index and the change in the NASDAQ Composite index. Both variables are significant in both periods. The effect of the ΔFnG index changed its sign from positive in the first subperiod (01.02.2018-31.12.2020) to negative in the second one (01.01.2021-31.07.2022). We assume that this change is associated with the fact that during the 1st subperiod the FnG index was mostly below the level of 50 (the market was skeptical towards the Bitcoin perspectives) and there was a lot of space for the further increase in prices and returns. The 2nd subperiod started with the levels of the FnG index which were close to the maximum (the market was too optimistic, overheated) and there was not enough space for the further increase in the returns. Each additional percent to the ΔFnG index didn't met the proportional response from the BTC returns. Also, we found out that during the 2nd subperiod the changes in Bitcoin prices were more sensitive to the negative changes in the FnG index (index falls) rather than to the positive ones. Considering the fact that the sum of the negative changes of the FnG index outweighs the sum of the positive changes in the 2nd subperiod, we can state the greater sensitivity of the ΔBTC price to the negative changes in the FnG index contributed to the greater BTC price changes in the 2nd subperiod.

The changes in the NASDAQ Composite index were also significant to the changes in the Bitcoin price, its effect didn't change its sign (being always positive). The effect of this factor increased in the 2nd subperiod significantly reaching the level of 0.9167 (each additional percent to the percentage change of the NASDAQ index increased the change in the Bitcoin prices on 0.9167 %) and was far greater than the effect of the ΔFnG index.

So, we can say that the main factors which caused the greater changes in the Bitcoin prices in the 2nd subperiod (01.01.2021-31.07.2022) were changes in the

NASDAQ index and “fear and greed” index. The hypothesis that the stock returns are uncorrelated with the BTC returns is rejected. The strong correlation between the ΔNASDAQ and ΔBTC is evident.

The thesis results can be applied in the following ways:

- high levels of the “fear and greed” index (close to 90-100) can be regarded as the sign that the market is overheated, there is no place for the further increase in the returns (the price can grow with a constant speed, stay the same or fall). The decrease of the BTC price is the most likely scenario and it can be treated as a time to close the position;
- low levels of the “fear and greed” index (less than 25) tell us that the market is too pessimistic about the Bitcoin perspectives, there is a lot of space for the increase in prices and returns. That can be regarded as a right time to enter the market;
- high correlation with the NASDAQ index in the 2nd subperiod tells us that the market started to treat Bitcoin as a risky tech stock;
- Bitcoin price changes can be influenced by the same factors as the changes in the NASDAQ index (Fed rate, the inflation expectations and the market sentiment towards the tech sector);
- due to high correlation with the NASDAQ (almost one to one) Bitcoin can’t serve as a hedge against the loses in the NASDAQ in the portfolio. The low correlation which was present till the 2021 year can’t guarantee that it will lower in the future.

We recommend to base the decision to buy or sell Bitcoin on the value of the “fear and greed” index, the current level of the Fed rate, the inflation expectations and the investment strategy. Bitcoin can be included to the portfolio as a hedge against the loses in the NASDAQ index only when their correlation lowers. For now its too high.

Despite the significance of our OLS regressions’ coefficients the R^2 value remains quite low (approximately 0.10). We can’t use our model for the prediction of the Bitcoin price changes. Further research can focus on identifying other factors affecting the ΔBTC price. Taking into account the increased correlation between ΔNASDAQ index and ΔBTC price among those factors could be the Fed rate, the inflation expectations, market sentiment towards tech stocks etc.

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APPENDIX A. DESCRIPTIVE STATISTICS

Variables	Observations number	Mean	Standard deviation	Min	Max
All periods (February 01, 2018 – July 31, 2022)					
ret_btc, %	1642	0.0578	3.9129	-46.4730	17.1821
d_n_paym, %		-0.0058	11.4663	-41.0745	40.4354
d_addres, %		-0.0061	16.4807	-45.0848	41.4091
d_hash, %		0.4387	3.5706	-13.2377	9.2570
d_fng, %		0.0685	22.2447	-140.8767	188.707
d_nas, %		0.034	1.571	-13.1491	8.9347
d_VIX, %		-0.490	8.8633	-40.4882	48.0214
First period (February 01, 2018 – December 31, 2020)					
ret_btc, %	1066	0.1101	3.8490	-46.4730	16.7104
d_n_paym, %		0.0285	11.7521	-41.0745	35.7487
d_addres, %		0.0360	16.928	-43.6707	41.4091
d_hash, %		0.5502	3.4761	-11.9821	9.2570
d_fng, %		0.1769	22.5887	-140.8767	188.707
d_nas, %		0.0439	1.581	-13.1491	8.9347
d_VIX, %		-0.5606	8.8947	-35.9888	43.8432
Second period (January 01, 2021 – July 31, 2022)					
ret_btc, %	576	-0.0392	4.025	-17.4053	17.1821
d_n_paym, %		-0.0428	10.8706	-30.5076	40.4354
d_addres, %		0.0198	15.600	-45.0848	40.380
d_hash, %		0.2122	3.7227	-13.2377	8.4237
d_fng, %		-0.1375	21.6504	-83.2909	93.6093
d_nas, %		0.0155	1.558	-5.1206	3.9830
d_VIX, %		-0.3603	8.8265	-40.4882	48.0214

APPENDIX B. CORRELATION TABLE

All periods (February 01, 2018 – July 31, 2022)

	ret_btc	d_n_paym	d_addres	d_hash	d_fng	d_nas	d_VIX
ret_btc	1.00	0.01	0.04	0.04	0.04	0.26	-0.14
d_n_paym	0.01	1.00	-0.05	-0.04	0.00	0.01	0.05
d_addres	0.04	-0.05	1.00	0.01	0.01	0.03	-0.05
d_hash	0.04	-0.04	0.01	1.00	0.03	-0.01	0.02
d_fng	0.04	0.00	0.01	0.03	1.00	0.03	-0.06
d_nas	0.26	0.01	0.03	-0.01	0.03	1.00	-0.59
d_VIX	-0.14	0.05	-0.05	0.02	-0.06	-0.59	1.00

First period (February 01, 2018 – December 31, 2020)

	ret_btc	d_n_paym	d_addres	d_hash	d_fng	d_nas	d_VIX
ret_btc	1.00	0.03	0.04	0.04	0.10	0.20	-0.07
d_n_paym	0.03	1.00	-0.07	-0.04	-0.03	0.02	0.04
d_addres	0.04	-0.07	1.00	0.02	-0.01	0.04	-0.05
d_hash	0.04	-0.04	0.02	1.00	0.05	0.03	0.00
d_fng	0.10	-0.03	-0.01	0.05	1.00	0.03	-0.08
d_nas	0.20	0.02	0.04	0.03	0.03	1.00	-0.54
d_VIX	-0.07	0.04	-0.05	0.00	-0.08	-0.54	1.00

Second period (January 01, 2021 – July 31, 2022)

	ret_btc	d_n_paym	d_addres	d_hash	d_fng	d_nas	d_VIX
ret_btc	1.00	-0.02	0.04	0.02	-0.07	0.37	-0.27
d_n_paym	-0.02	1.00	-0.03	-0.03	0.07	-0.02	0.07
d_addres	0.04	-0.03	1.00	0.01	0.05	0.03	-0.06
d_hash	0.02	-0.03	0.01	1.00	-0.01	-0.07	0.06
d_fng	-0.07	0.07	0.05	-0.01	1.00	0.04	-0.02
d_nas	0.37	-0.02	0.03	-0.07	0.04	1.00	-0.69
d_VIX	-0.27	0.07	-0.06	0.06	-0.02	-0.69	1.00