Price determinants and prediction of Bitcoin and Ethereum

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ABSTRACT

This paper studies the two biggest cryptocurrencies by their market capitalization: Bitcoin and Ethereum. Following the common practice of the existing literature, I select certain macroeconomic variables that are likely to affect their price returns. The model used in the paper is an extension of the Autoregressive Conditional Heteroskedasticity model. The estimations show that the S&P, SSE, Nikkei, Cyber 15, gold and oil price returns are significant for the models, with some of these variables being common for both.

Keywords: Bitcoin, Ethereum, returns, GARCH, predictions

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All the remaining errors in this paper are mine.

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Introduction

A little less than a decade ago, on January 3rd 2009, the Bitcoin system has been created and the first block, known as block number 0, was mined. At the time it had a value of $0. The first transaction involving Bitcoins took place in 2010, when 10 000 Bitcoins were spent to order two pizzas worth 25$, with each Bitcoin valued slightly more than zero dollars. Some seven years later, in late 2017, Bitcoin's price was at its all time peak of $18 000 USD. As of now, April 12, 2018, those 10 000BC have a value of more than $76 million, with each Bitcoin valued at $7600. Over the last year alone Bitcoin's market capitalization has increased 7 times, currently standing at $129 billion. This data shows one of the reasons the Bitcoin market has attracted so much attention.

With the increasing popularity of Bitcoin the amount of academic research about Bitcoin has also increased. Some researchers focused on the behavioral aspects of Bitcoin purchases. Others speculated whether Bitcoin market is a bubble that is about to pop, and tried to understand what is the fundamental value behind its price. Bitcoin has been compared to both money and financial assets, as it has characteristics from both. Another big chunk of Bitcoin literature focuses on the impact Bitcoin has on financial markets, as well as on the exogenous factors affecting Bitcoin.

Undoubtedly, Bitcoin is the most successful, prominent, and, perhaps, controversial cryptocurrency in the market, but it is by far not the only one. At the moment of writing this, there are 1568 different cryptocurrencies, traded on 10288 markets, with a total market capitalization of approximately $330 billion. Top 15 cryptocurrencies make up 85-90% of the total market cap, with Bitcoin alone comprising 43% of it. Other cryptocurrencies, collectively known as altcoin, have not received as much attention as Bitcoin has, and the relationship between them is unclear. It is important to point out that each cryptocurrency is different from Bitcoin, with its own advantages and disadvantages. So, is Bitcoin the "leader" for altcoin and determines the overall movements in the cryptocurrency market, or are they substitute for Bitcoin, being unaffected by Bitcoin or even moving in the opposite directions. Historical evidence shows that it depends on the time period and cryptocurrency. When Bitcoin prices surge, it may either increase market confidence and take altcoins along, or suppress them. Likewise, when Bitcoin stagnates, it can either cause stagnation in others, as investors are unsure of the market's direction, or make them boom, as happened in late 2017/early 2018. On the graph below we can see that in the abovementioned period, altcoins' market cap increased, while Bitcoin's sunk.

Figure 1: Historical market capitalization of cryptocurrencies. (taken from coin.dance)

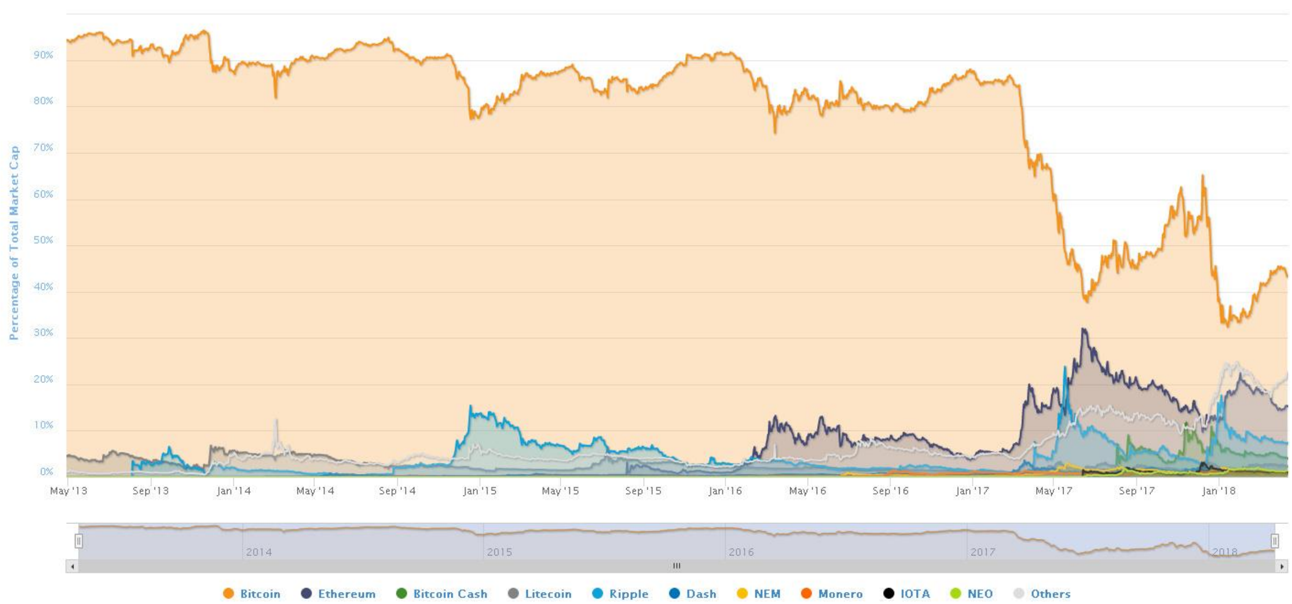
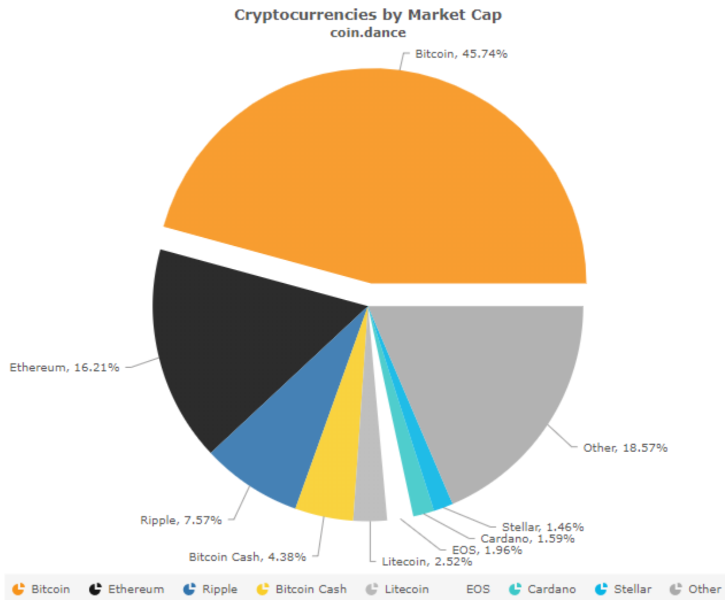


Figure 2: Current market cap of cryptocurrencies.



To try to understand the relationship between them, I will develop models predicting the price returns of Bitcoin and Ethereum, the second largest altcoin. I will try to find differences and similarities in the way they respond to the explanatory variables, and their volatilities using the GARCH method. This paper consists of several sections. First, I will briefly explain the technology behind cryptocurrencies. Then, I will review the literature used for my research. Consequently, I will present the data and methodology for my model, followed by estimations and results.

Motivation

The Bitcoin market, as well as cryptocurrency market in general, is extremely volatile. The situation in the cryptomarket can change drastically within a month, let alone a year. Thus, academic papers may become obsolete and not practically relevant several months after their publication. Moreover, while Bitcoin gets increasingly more attention, other cryptocurrencies slip under the radar. They have only a small fraction of the research conducted for Bitcoin. Finally, there is no absolute model predicting the price determinants of Bitcoin, and the relationship between Bitcoin and altcoin price movements. Perhaps there is even no model predicting the market, due to its speculative nature. My contribution in this paper is that I will keep the research up to date, try to define a relevant model, and compare the response of Bitcoin's, and Ethereum's, as a representative of other cryptocurrencies, to those variables. My methods will closely follow the best practices and recommendations identified in the reviewed literature.

Technology behind Bitcoin: Blockchain

For millennia people have used physical tokens as the medium of exchange. In this case the transaction occurs immediately, but the physical presence of both parties in the same location is required. However, in the last few decades digital transactions became extremely widespread. In the digital payment systems money is represented as a sequence of bits. For example, if Gor sends a money file to Anahit, the moment Anahit opens the file the money is transferred to her account. However, if Gor also sends money to Arman, there is a risk that he will send the same money file he had sent to Anahit, and in that case either Arman or Anahit, depending on who opens the file the last, will have no money received. This is called the double spending problem (Ólafsson, 2014). To avoid this problem an independent third party, like PayPal, must confirm the transactions. Yet, it is not always convenient to find a trusted third party, and even if there is one, they may charge high transaction costs. Payments with cryptocurrencies allow transactions to be validated without a third party, while avoiding double spending problem and transaction costs. This is what makes such payments so attractive to users. Exactly this was the motivation of the original publisher of the Bitcoin paper, a person or a group of programmers under the pseudonym Satoshi Nakamoto, who introduced the first cryptographic transaction system using a peer-to-peer distributed network (Nakamoto 2008). So how does the system work?

First, I will bring the definition of cryptocurrency. Cryptocurrency is defined as “a digital asset designed to work as a medium of exchange using cryptography to secure the transactions and to control the creation of additional units of the currency” (Sovbetov 2018). Bitcoins are recorded as transactions, and each Bitcoin can be tracked back through its history. For example, Gor wants to send 1 Bitcoin to Anahit. Anahit can verify that Gor had received that 1 Bitcoin from Arman previously, and that Gor had not spent it and is, thus, able to pay her. When Gor publishes a message that he wants to sell his Bitcoin to Anahit, that message is encrypted with his private key, which is like a digital signature. The Bitcoin network identifies Gor and Anahit by their pubic keys, which are similar to account numbers (Böhme, et.al, 2015).

As the system has no supervisors, it is up to the users to record and verify transactions. The users are encouraged to solve mathematical puzzles to record transactions and keep them updated. Such users, called miners, are awarded with newly “mined” Bitcoins, as well as small transaction fees. The user who first solves the puzzle will record the transaction and receive a reward. Thus, the higher computational power of miners’ computers, the more probable they are to record transactions and earn Bitcoins. Once a transaction is recorded, it is published in a “block”, which contains a proof-of-work that the puzzle was solved. Each block is built upon the previous one, and contains the data on all the new transactions that happened after the solving of the last puzzle. After other users confirm that the solution is correct, they start working on a new block. In this way a chain of blocks, blockchain, is created, which ensures the chronological order of all the blocks and, thus, transactions. As the verification process takes approximately 10 minutes, and the system may require up to 6 verifications, a delay of up to an hour may be created until the transaction is validated.

The supply of Bitcoins is limited by Satoshi to 21 million, and it is predicted to reach the limit by 2035 (Berentsen, 2018). As the reward for miners approaches to zero as the number of Bitcoins increases, more and more transactions include fees. These fees are, nevertheless, much less than those of banks or other conventional third parties. But as mathematical puzzles become harder, a higher computational capacity will be required to solve them, and thus miners will face a higher electricity cost. This is likely to drive up the transaction fees over time (Böhme, et.al, 2015).

Bitcoin has a number of unique characteristics. First, it is decentralized and is not regulated by anything other than its underlying software. It does not require a verification of users' identity, thus increasing privacy. Users can additionally ensure their privacy by using *mixers* for a small fee, which will make their transactions' history untraceable. Bitcoin has no bans on sales of certain goods, even illegal ones. And finally, its transactions are irreversible, which is done to keep the system simple, despite causing potential problems for users (Böhme, et.al, 2015.) Although some of these characteristics gave incentives for conducting illegal transactions, cryptocurrencies are being used in a number of other ways. They can serve as a medium of exchange, especially for currency; digital wallets, financial investments, and other purposes. More and more countries and companies start accepting cryptocurrencies. Coincidentally, exactly today, April 12, 2018, a Spanish bank Santander launched first banking blockchain retail payments application.

Ethereum is similar to Bitcoin in its underlying technology. It uses the same, although slightly modified, version of Nakamoto's original system. Its main advantage over Bitcoin is that transaction verification time is 15 seconds, compared to 10 minutes in Bitcoin, and the median fee is just $0.33, compared to $23 for Bitcoin. Ethereum was created as a platform for *smart contracts*. Without going into technical details, smart contracts with Ethereum's cryptographic code offer more flexibility and convenience in transactions between users, as compared to transaction done through the Bitcoin system.

The system of Ethereum went live on early August 2015. In 2016 the community decided to hard-fork the system. Hard-fork happens when the developers decide to apply such changes to the system so that the old and new versions become incompatible. As a result Ethereum divided into two separate cryptocurrencies. The new one retained the name Ethereum (ETH), while the old system became known as Ethereum Classic (ETC). In this paper I take the new version of Ethereum (ETH).

Literature review

The number of academic studies on Bitcoin has increased significantly over the last two years. The volatile and unpredictable nature of the market, as well as its increasing potential impact not only on individual users and businesses, but also countries and international relations, put Bitcoin in the centre of much attention. Here I describe some of the recent academic researches on Bitcoin, with the full list of used literature being at the end of this paper.

The first paper I review here aims to explore Bitcoin's price determinants using Bayesian structural time series (Poyser, 2017). The author divides cryptocurrency price determinants into two groups: internal and external. Internal factors are associated with supply and demand, and include transaction costs, reward systems, computational power for mining, and rules of the system. External factors are attractiveness (popularity, trend), macro-financial factors (exchange rates, oil and gold prices, stock markets, interest rates, expectations), and political (adoptions or bans of cryptocurrency usage by countries). His estimations show that Bitcoin price is negatively related to CNY/USD rate, sentiments, and gold price, and positively with USD/EUR rate, attractiveness, and stock indexes. He concludes that Bitcoin is highly speculative.

Several papers compared Bitcoin to money or financial assets. One such paper compared it to gold and USD (Dyhrberg, 2015). She chooses USD/EUR and USD/GBP rates, gold cash and futures rates, FTSE index, and the Federal funds rate. She found that Bitcoin has similarities with both gold and USD, as similar to them, Bitcoin can be used in risk management, reacts to similar exogenous variables, has hedging capabilities, and shows symmetrical response to good and bad news. Dyhrberg concludes that Bitcoin can be used for portfolio management. Another paper suggests that its extraordinary volatility is the main obstacle for Bitcoin becoming an alternative to fiat money (Cermak, 2017). The author builds a GARCH model with macroeconomic variables (exchange rates, government bonds, stock indexes) of the countries where Bitcoin is traded the most (USA, China, EU countries, Japan), and shows that Bitcoin shows statistical dependence from the economies of these countries. He concludes that without a centralized regulation, Bitcoin will remain volatile and will not be able to become money.

In his paper Schut discusses how the changes in Bitcoin market change it as an investment tool (Schut, 2017). He included trading volume, three proxies for economic uncertainty (VIX, EPUI, CCI), a number of US macroeconomic variables, and exchange rates of USD with 8 different currencies, to build three models. S&P500 was the only variable that was significant in all of them, with other variables' significance varying between models. He concludes that due to maturity of Bitcoin, its prices start to reflect the overall economy of the USA, making it more predictable, and thus more feasible as a financial asset.

Another big part of literature focuses on Bitcoin price volatility and price determinants. In his paper Julio Estrada finds that Bitcoin volatility and VIX show bidirectional Granger-causality, and that Bitcoin prices depend on Blockchain trends and S&P 500 (Estrada, 2017). In yet another paper Katsiampa finds that the best model is AR-GARCH model, as it emphasizes both short-run and long-run components (Katsiampa, 2017). In a similar paper, the best GARCH models for analyzing cryptocurrencies are found to be IGARCH and GJRGARCH (Chu et al., 2017).

In the paper by Giaglis et al., it is concluded that Bitcoin prices show correlation with Wikipedia search inquires, mining difficulty (technically known as *hash rate*), and USD/EUR rate in the short run, while with Bitcoin supply and S&P500 index in the long run (Giaglis et al., 2015).

The last paper reviewed, which is the latest published from those reviewed, trading volume, volatility, and market beta are found to have a statistically significant effect on cryptocurrencies' prices in the short-run, while attractiveness and S&P 500 shows correlation in the long-run (Sovbetov, 2018).

Looking through literature made it clear that different papers show different results on the same subject, oftentimes using the same explanatory variables. This may be explained by rapidly evolving cryptocurrency market, as researches done at different time points give different outcomes. This is one of the reasons why it is important to keep the academic studies up-to-date, which I aim to achieve with this paper. I will incorporate different aspects from the reviewed literature in building my model.

Data and Methodology

Data description

The paper covers the period from August 7, 2015 to April 4, 2018, making the total number of observations equal to 972. Although the data for most of my variables spans over many years, the starting point is chosen to be August 7, 2015 based on the first available data on Ethereum, so as to keep the number of observations for all variables equal. The endpoint data is simply the date when I collected my data.

My first dependent variable is the price of Bitcoins in USD. The price is the opening daily price taken from the biggest trading markets such as Bitfinex and Bitfinance, which together comprise almost 10% of the trade. Although the prices of the biggest markets have more weight, the price taken is the average of several leading markets. This is a useful way of calculating given considerable disparities in prices on different markets. The data is downloaded from coinmetrics.io, which takes the information from coinmarketcap.com as its source.

The dependent variable from my other model is exchange rate of Ethereum to USD, i.e. the price of Ethereum. Much like its Bitcoin counterpart, it is the daily opening price calculated in the same way and is taken from the biggest Ethereum trading markets, such as Bitfinex and OKEx. The data is retrieved from the same source.

According to the definitions given above, my other variables are among external macro-financial cryptocurrency price determinants. Thus, I omit many important variables, like search trends, transaction fees, hash rates, sentiments, and regulations to keep my model relatively simple.

Next I have two exchange rates of USD, first to Euro (EUR) and then to Chinese Yuan (CNY). The theoretical research shows that the areas that have the most trade in cryptocurrency market after the USA are the European countries and China. This is the reason why I chose exactly these two rates. The data is retrieved from investing.com.

Further I have several stock indexes. All of them are downloaded from investing.com. First index is Standard and Poor's 500, or simply S&P, which is an American stock market index. It is calculated on the basis of the 500 large companies that have their stocks listed on NASDAQ or NYSE. The second is the Dow Jones Industrial Average. Dow is calculated based on the trade of stocks of 30 large publicly owned US based companies. The two indexes together reflect the overall economy of USA, the biggest market for cryptocurrencies.

Following the logic, I took three other stock indexes of other countries. First is the Financial Times Stock Exchange 100 Index, or FTSE. The share index incorporates 100 firms with the highest market capitalization listed in London Stock Exchange. The index can be a good proxy for the

European economy. Second is the Shanghai Stock Exchange Composite index, or SSE Index. The index is a weighted composite price index of all the stocks traded in the eponymous stock exchange, and is calculated using Paasche formula. Finally I took the Nikkei 225 Index. As the name suggests, it is a price-weighted index with 225 constituents whose stocks are traded in Tokyo Stock Exchange. SSE and Nikkei 225 are estimates for the Chinese and Japanese economies respectively. As both these countries are among the top cryptocurrency trading countries, I consider them relevant.

My eighth independent variable is the West Texas Intermediate (WTI) crude oil daily price per barrel in USD. The data is taken from fred.stlouisfed.com. As USA is the largest oil consuming country, oil prices of a company that produces domestically consumed oil are a good indicator. Historical evidence shows that there is usually a correlation between oil and stock prices and economic activity.

The next variable is the gold price per troy ounce (31.2g) in USD. The data is retrieved from gold.org. Gold is a well-known and established financial asset, often used for hedging.

Further, I have two variables which are proxies for economic uncertainty. First is the Chicago Board Options Exchange Volatility Index (CBOE VIX), which is a measure of the S&P 500 30 day index options volatility. Informally VIX is referred to as fear index. The second is the Economic Policy Uncertainty Index (EPUI) for USA. It incorporates media coverage on policy-related events, disagreements about economic forecast, and federal tax code provisions. Both variables' data is daily and taken from investing.com.

My last variable is the Cyber 15 Index. The index is computed by me, incorporates the first 15 cryptocurrencies by market capitalization and is the sum of their weighted prices. The index will show the overall movement in cryptocurrencies prices. As the first 15 cryptocurrencies make up more than 90% of the market, it is a pretty accurate estimator. Data is taken from coinmetrics.io.

The data on most of the explanatory variables had no values for weekends and other holidays, while the data for Bitcoin and Ethereum prices comprises all days of the week and had no breaks in-between. To align my data, I filled the missing values of those variables, using the values of the previous known day. This may have caused a slight distortion in the data.

In my model I will use the returns on the variables. Returns are calculated by taking the natural logarithm of the numerical value, and taking the difference with the previous period. This is just a way to measure the change from one period to another. The descriptive statistics of the data can be found in the Appendix. It is noteworthy that Ethereum returns have both a higher mean and standard deviation as compared to Bitcoin, meaning that on average they had higher returns, but were more volatile.

After doing the literature review, I find it hard to form any expectations about any given variable, as the results tend to differ in different papers. Nevertheless, I expect that these variables will describe Bitcoin better than Ethereum, for Bitcoin is a more mature cryptocurrency and will thus respond more to the variables that usually affect financial assets.

Methodology

My models will have the following form:

$$bret = \beta_0 + \beta_1 spret + \beta_2 djret + \beta_3 ftseret + \beta_4 sseret + \beta_5 nikret + \beta_6 oilret + \beta_7 ueret + \beta_8 uyret + \beta_9 goldret + \beta_{10} cybret + \beta_{11} vixret + \beta_{12} puiret + u$$

$$eret = \beta_0 + \beta_1 spret + \beta_2 djret + \beta_3 ftseret + \beta_4 sseret + \beta_5 nikret + \beta_6 oilret + \beta_7 ueret + \beta_8 uyret + \beta_9 goldret + \beta_{10} cybret + \beta_{11} vixret + \beta_{12} puiret + u$$

As one can see, all variables have *ret* at the end of each variable, which stands for returns. As described above, it simply indicates that the variables are not in level form, but in percentage changes. The two models are completely identical except for the dependent variables, which are the Bitcoin and Ethereum returns in the first and second models respectively. As it will turn out, these models give poor results, therefore new models will be suggested later. The explanatory variables stand for S&P 500 index, Dow Jones index, FTSE 100 index, SSE index, Nikkei 225 index, oil price per barrel in USD, USD/EUR rate, USD/CNY rate, gold price per ounce in USD, Cyber15 index, VIX, and EPUI.

The model I will use in this paper is the generalized autoregressive conditional heteroskedasticity model, i.e. GARCH. The model is an extension of the ARCH model, which was first developed by Robert Engle in 1982. In the standard model of OLS one of the assumptions is that of constant variance for any given values of explanatory variables, in other words we assume homoscedasticity. However, in reality our data is often heteroscedastic, which will cause our estimators from regressions be, albeit still unbiased, not correct. To be more specific the coefficients' standard errors will usually appear smaller, and this will create a false perception of precision. The Gauss-Markov assumptions, thus, do not hold. For ARCH models, heteroskedasticity is a necessary condition, and it does not only correct OLS results, but also allows making predictions on heteroscedastic models. According to ARCH model the volatility can be estimated with more precision if we take into account the data on previous periods. In other words, volatility is conditional on the volatility of previous periods: hence its name. Before ARCH it is useful to understand the Autoregressive Moving Average model (ARMA) model.

For building the model we need 2 equations: mean equation and variance equation. Both of these must be estimated simultaneously. For ARCH (1) the mean and variance equations have the following form:

$$y_t = \phi + \epsilon_t$$
$$\epsilon_t | I_{t-1} \approx N(0, \sigma_t^2)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$$

The error variance equation of ARCH has the following general form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2$$

where p is the number of lags of squared residuals taken into account, and ε is the residual of the given periods. p is the AR component, and is written as ARCH (p). We also need the coefficients to be positive to ensure positive variance, and their sum to be less than 1, so as the series does not explode.

To incorporate the variance of the previous periods as well, we need the GARCH model. A useful parametrization of ARCH model, it was introduced by Engle's student, Tim Bollerslev, in 1986. The general form of the conditional variance equation is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + ... + \beta_q \sigma_{t-q}^2$$

where q is the number of lags of variances we take into account.

What is of interest is the sum of all α-s and β-s, which shows how long does it take for large volatilities to decay. In other words, GARCH model shows the time-varying volatility clustering. Volatility clustering is defined as a period of large volatilities after large volatilities, or small volatilities after small volatilities. Volatility clustering also means that the residuals are conditionally heteroscedastic. After having the mean and variance equation, we can add explanatory variables as in the case of OLS method.

Estimation and Results

When dealing with time-series it is crucial to be sure that the data is stationary. Stationary data has the following statistical properties:

$$\begin{aligned} E(y_t) &= \mu \quad && \text{(constant mean)} \\ \operatorname{var}(y_t) &= \sigma^2 \quad && \text{(constant variance)} \\ \operatorname{cov}(y_t, y_{t+s}) = \operatorname{cov}(y_t, y_{t-s}) &= \gamma_s \quad && \text{(covariance depends on } s \text{, not } t\text{)} \end{aligned}$$

If the data in non-stationary we may have a spurious regression, i.e. we obtain significant regression results from unrelated data. Non-stationarity may also cause the data to “explode”. In order to check my variables for stationarity I use the Augmented Dickey-Fuller tests. The results show that neither of our variables is non-stationary, so I proceed to the next step. The table with the tests can be found in the Appendix. The reason they are stationary, which is usually not the case with financial time-series data, is that I have already made the transformation of my level data to the percentage change, which would remove non-stationarity.

My initial models, in the way they are depicted in the methodology section, turned out to be poor models, as all but one variables were insignificant, and the models gave bad predictions. The preliminary results can be found in the Appendix. Consequently, I experimented with different models and came up with two other models that are more refined. The lags on explanatory variables were chosen by trial-and-error, so as to achieve the highest significance. I should mention that the significance of the variables I speak of is the one from the GARCH models, not OLS. I will first show the model for Bitcoin, and then the one for Ethereum, with all the steps I have done.

The new Bitcoin model and its OLS regression can be found below.

$$bret = \beta_0 + \beta_1 vixret_{t-10} + \beta_2 nikret + \beta_3 sseret + \beta_4 spret + \beta_5 uyret + \beta_6 cybret_{t-4} + \beta_7 goldret_{t-1} + \beta_8 oilret_{t-5}$$

Table 1: OLS of the model for bret.

bret	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
vixret						
L10.	.0185741	.0179669	1.03	0.301	-.0166849	.0538331
nikret	.0949006	.1220265	0.78	0.437	-.1445701	.3343713
sseret	-.1030406	.1256011	-0.82	0.412	-.3495264	.1434451
spret	.286624	.1928162	1.49	0.137	-.0917678	.6650159
uyret	.4144214	.7585607	0.55	0.585	-1.074215	1.903058
cybret						
L4.	.0037753	.0285031	0.13	0.895	-.0521605	.0597111
goldret						
L1.	.3445379	.1834943	1.88	0.061	-.0155601	.7046359
oilret						
L5.	-.0338267	.064488	-0.52	0.600	-.1603811	.0927276
_cons	.0032928	.0013176	2.50	0.013	.0007071	.0058785

Before moving forward I will perform the Breusch-Godfrey test for autocorrelation for the first 25 lags. The results are as follows:

Table 2: Breusch-Godfrey test for autocorrelation of bret.

Breusch-Godfrey LM test for autocorrelation

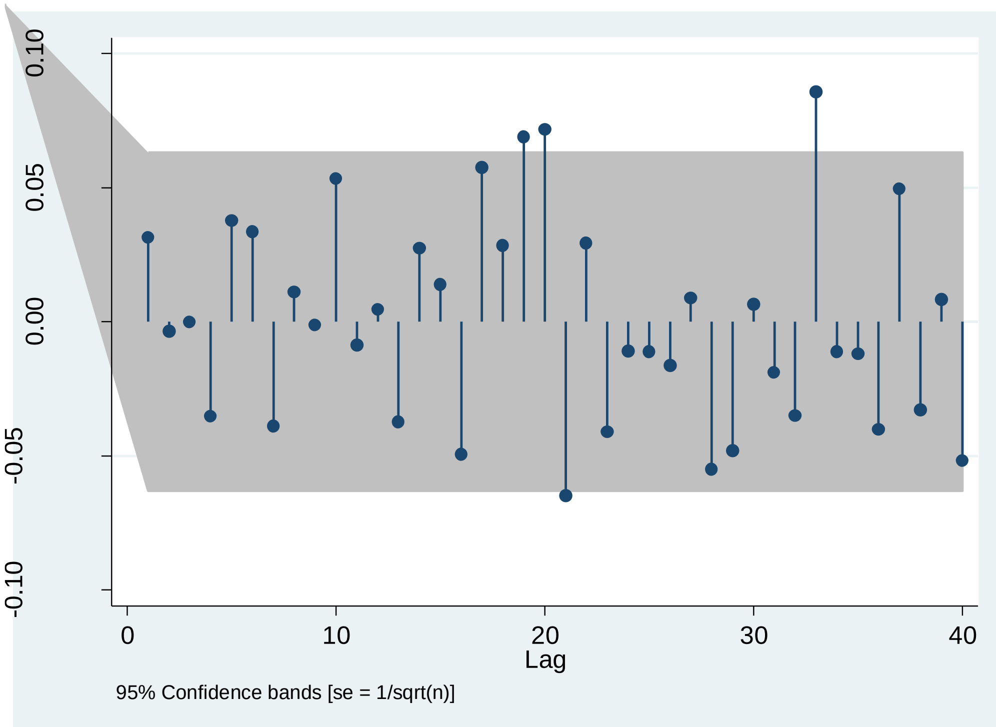
lags(p)	chi2	df	Prob > chi2
1	0.973	1	0.3238
2	0.986	2	0.6107
3	0.986	3	0.8045
4	2.177	4	0.7033
5	3.573	5	0.6124
6	18.841	6	0.0044
7	20.239	7	0.0051
8	20.279	8	0.0093
9	20.289	9	0.0162
10	22.861	10	0.0113
11	22.937	11	0.0180
12	22.937	12	0.0283
13	24.521	13	0.0267
14	25.157	14	0.0330
15	25.220	15	0.0471
16	27.403	16	0.0372
17	30.377	17	0.0238
18	30.805	18	0.0303
19	34.402	19	0.0165
20	38.801	20	0.0071
21	42.994	21	0.0031
22	43.885	22	0.0037
23	45.965	23	0.0030
24	46.240	24	0.0041
25	46.448	25	0.0057

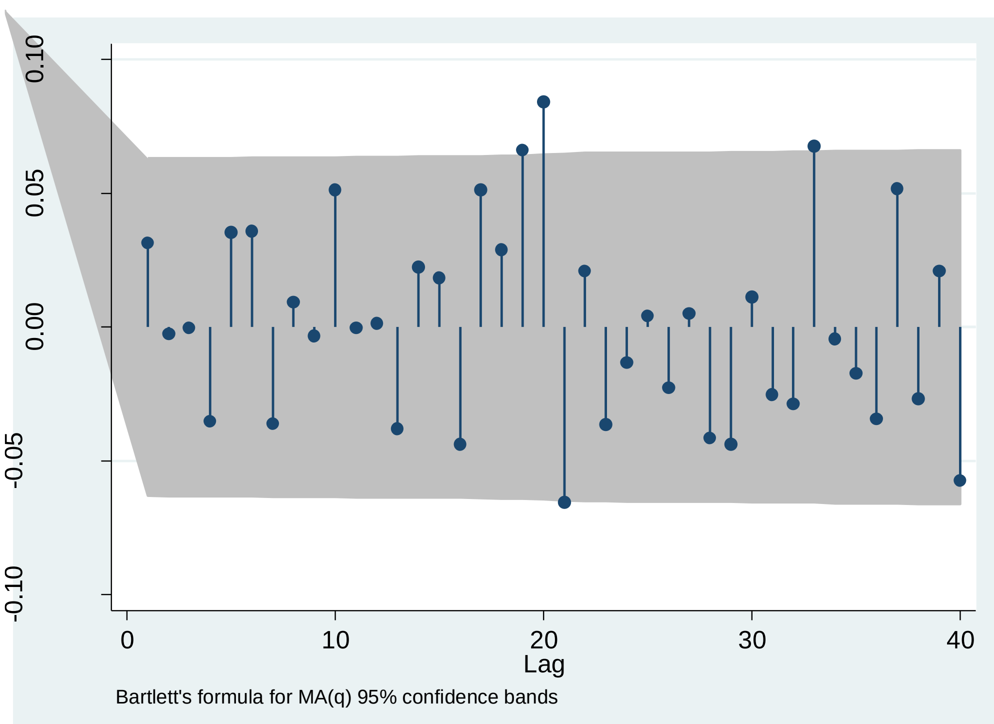
H0: no serial correlation

As we can see, we fail to reject the null hypothesis that there is no serial correlation for the first five lags, which means the data is not autocorrelated. However, after that all the lags are autocorrelated. This means that an ARMA model will be a better one.

To build the ARIMA model I first need to identify the AR and MA components. To get the order of AR I draw the partial autocorrelation function (PACF), and for the order of MA I draw the autocorrelation function (ACF).

Figure 3: PACF and ACF of bret.





Both graphs show that lags 19 and 20 are significant. Nevertheless, running several models with different orders of p and q showed that ARMA (2, 2) is appropriate. Although it does not have the lowest AIC or BIC, but, if considered together, that model has the lowest numbers. In other words, there are models that have lower AIC, but much higher BIC, or lower BIC, but much higher AIC. This model has both pretty low. What regards the p-values of the variables, it makes little sense choosing the models based on them, especially if they are used not only for explanation, but also prediction (Shmueli, 2010). Thus, I estimate ARIMA (2, 0, and 2) model.

Table 3: ARIMA model for Bitcoin returns.

bret	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
bret						
vixret						
L10.	.0203309	.0184999	1.10	0.272	-.0159282	.0565901
nikret	.0963977	.1500369	0.64	0.521	-.1976693	.3904647
sseret	-.1132392	.1359475	-0.83	0.405	-.3796913	.153213
spret	.278266	.1832329	1.52	0.129	-.080864	.6373959
uyret	.3770214	.6971226	0.54	0.589	-.9893138	1.743357
cybret						
L4.	.0047857	.0246801	0.19	0.846	-.0435864	.0531579
goldret						
L1.	.3445621	.2154137	1.60	0.110	-.077641	.7667651
oilret						
L5.	-.0328673	.0822621	-0.40	0.689	-.194098	.1283634
_cons	.0032877	.001379	2.38	0.017	.0005849	.0059906
ARMA						
ar						
L1.	-.3631885	5.291487	-0.07	0.945	-10.73431	10.00794
L2.	.1165764	1.851879	0.06	0.950	-3.513039	3.746192
ma						
L1.	.3960981	5.292327	0.07	0.940	-9.976672	10.76887
L2.	-.1121543	2.013	-0.06	0.956	-4.057563	3.833254
/sigma	.0405642	.0005359	75.70	0.000	.0395139	.0416145

In order to understand if this model has any issues I use the Portmanteau test for white noise. For doing that I need to predict the residuals, denoted as *arhat*, and generate $arhat^2$.The test will show if there is an autocorrelation between squared residuals. In order to determine the appropriate lag of the Ljung-Box test, I take ln (n) as the order, which is a common practice. In this case n is 972, which gives the value of lags of 7.

Table 4: White noise test of squared residuals.

Portmanteau (Q) statistic	=	139.4235
Prob > chi2(7)	=	0.0000

As we can see, we reject the null hypothesis that there is no serial correlation, meaning there is one. This implies that there is an ARCH effect. To be sure, I will also check for an ARCH effect by regressing the squared error on its lag.

Table 5: ARCH effect testing.

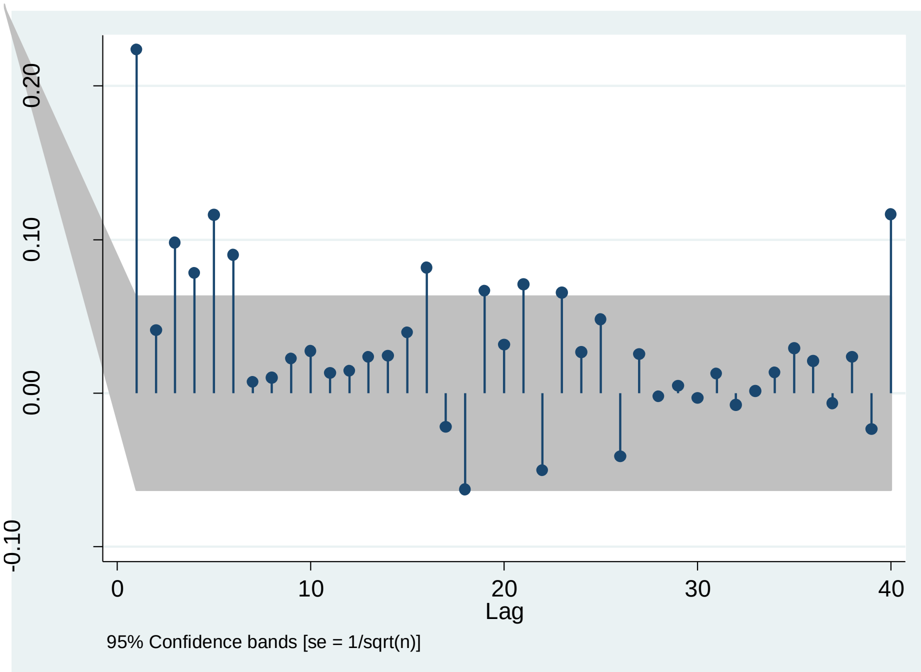
Source	SS	df	MS
Model	.000869341	1	.000869341
Residual	.016535281	962	.000017188
Total	.017404622	963	.000018073

Number of obs	=	964
F(1, 962)	=	50.58
Prob > F	=	0.0000
R-squared	=	0.0499
Adj R-squared	=	0.0490
Root MSE	=	.00415

arhat2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
larhat2	.2234829	.0314244	7.11	0.000	.1618146	.2851513
_cons	.0012795	.0001432	8.94	0.000	.0009985	.0015604

As the lag is statistically significant and larger than 0, there is an ARCH effect. Now I can be sure there is an ARCH effect, and will determine the orders of GARCH. The AR order will be determined by the PACF of the squared residuals.

Figure 4: PACF of the squared residuals.



The first lag is by far the most significant, so I will take it as the order. Numerous sources suggest that GARCH (1, 1) is the best model, so I will follow the common advice. The fact that I got the *p* order 1 further proves that it is the case. Not shown here, but ACF of the squared residuals also gave order of 1 as the most significant. Thus the model to be estimated is GARCH (1, 1). The decision was further proved to be correct by checking different models and comparing AIC and BIC. Here are the results.

Table 6: AR-GARCH model for Bitcoin price returns.

bret	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf. Interval]	
bret						
vixret						
L10.	.0220395	.0145897	1.51	0.131	-.0065558	.0506348
nikret	.193169	.0595906	3.24	0.001	.0763736	.3099643
sseret	-.232186	.0578481	-4.01	0.000	-.3455662	-.1188059
spret	-.160632	.1194035	-1.35	0.179	-.3946585	.0733945
uyret	.5585521	.4279627	1.31	0.192	-.2802394	1.397344
cybret						
L4.	.0493981	.0305469	1.62	0.106	-.0104728	.109269
goldret						
L1.	.1746828	.0923477	1.89	0.059	-.0063154	.355681
oilret						
L5.	-.0414261	.0375594	-1.10	0.270	-.1150412	.032189
_cons	.0023878	.0008458	2.82	0.005	.0007301	.0040454
ARMA						
ar						
L1.	-.2262521	8.169904	-0.03	0.978	-16.23897	15.78647
L2.	.2430499	4.537983	0.05	0.957	-8.651233	9.137333
ma						
L1.	.2666619	8.180585	0.03	0.974	-15.76699	16.30031
L2.	-.2528665	4.871346	-0.05	0.959	-9.800529	9.294796
ARCH						
arch						
L1.	.2050452	.0177234	11.57	0.000	.1703079	.2397824
garch						
L1.	.819511	.0117045	70.02	0.000	.7965706	.8424515
_cons	.000017	3.31e-06	5.13	0.000	.0000105	.0000234

Unfortunately, the sum of coefficients in ARCH is more than one, which shows non-stationarity. To overcome the issue, I set a constraint on the ARCH coefficients so that they are less than 1 (I set the constraint to be equal to 0.99 to be more precise), which makes the model Integrated GARCH (IGARCH). The new table is below.

Table 7: AR-IGARCH model for Bitcoin price returns.

bret	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
bret						
vixret						
L10.	.0239097	.0142906	1.67	0.094	-.0040993	.0519187
nikret	.2003972	.0625208	3.21	0.001	.0778586	.3229357
sseret	-.2422597	.0571438	-4.24	0.000	-.3542594	-.13026
spret	-.1496328	.1189209	-1.26	0.208	-.3827135	.083448
uyret	.4598064	.4239371	1.08	0.278	-.3710951	1.290708
cybret						
L4.	.0499996	.0273861	1.83	0.068	-.0036761	.1036752
goldret						
L1.	.1757633	.0977769	1.80	0.072	-.015876	.3674026
oilret						
L5.	-.0396502	.0385515	-1.03	0.304	-.1152097	.0359093
_cons	.0023899	.0008207	2.91	0.004	.0007814	.0039984
ARMA						
ar						
L1.	-.5894811	.44784	-1.32	0.188	-1.467231	.2882691
ma						
L1.	.6303004	.4319433	1.46	0.145	-.216293	1.476894
ARCH						
arch						
L1.	.1686423	.0114333	14.75	0.000	.1462334	.1910512
garch						
L1.	.8213577	.0114333	71.84	0.000	.7989488	.8437666
_cons	.0000243	3.69e-06	6.58	0.000	.0000171	.0000315

To further refine my model, I have decided to include vix_{t-1} and $usepui_{t-10}$ in the variance equation. This will show whether variance of those variables affects the variance of Bitcoin returns.

Table 8: AR-IGARCH model with modified variance equation for bret.

bret	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
bret						
vixret						
L10.	.02563	.0120886	2.12	0.034	.0019368	.0493231
nikret	.20533	.0439751	4.67	0.000	.1191403	.2915197
sseret	-.2696925	.0466032	-5.79	0.000	-.3610332	-.1783518
spret	-.2130088	.0950108	-2.24	0.025	-.3992265	-.0267911
uyret	.5277721	.3844214	1.37	0.170	-.22568	1.281224
cybret						
L4.	.0674833	.0272592	2.48	0.013	.0140563	.1209104
goldret						
L1.	.1752068	.0836453	2.09	0.036	.0112651	.3391485
oilret						
L5.	-.049028	.0285851	-1.72	0.086	-.1050537	.0069977
_cons	.0029399	.0006211	4.73	0.000	.0017226	.0041572
ARMA						
ar						
L1.	-.5742634	.305208	-1.88	0.060	-1.17246	.0239334
ma						
L1.	.6327111	.2884742	2.19	0.028	.0673121	1.19811
HET						
vix						
L1.	-.7555168	.0689894	-10.95	0.000	-.8907335	-.6203
usepui						
L10.	-.0411569	.0076539	-5.38	0.000	-.0561584	-.0261555
_cons	1.663959	1.034161	1.61	0.108	-.3629602	3.690878
ARCH						
arch						
L1.	.1646343	.0099357	16.57	0.000	.1451606	.184108
garch						
L1.	.8253657	.0099357	83.07	0.000	.805892	.8448394

Finally, I check the autocorrelation of errors of this model. For this I generate the residuals and variance of the model, and calculate standardized squared errors. Afterwards, I use Ljung-Box test.

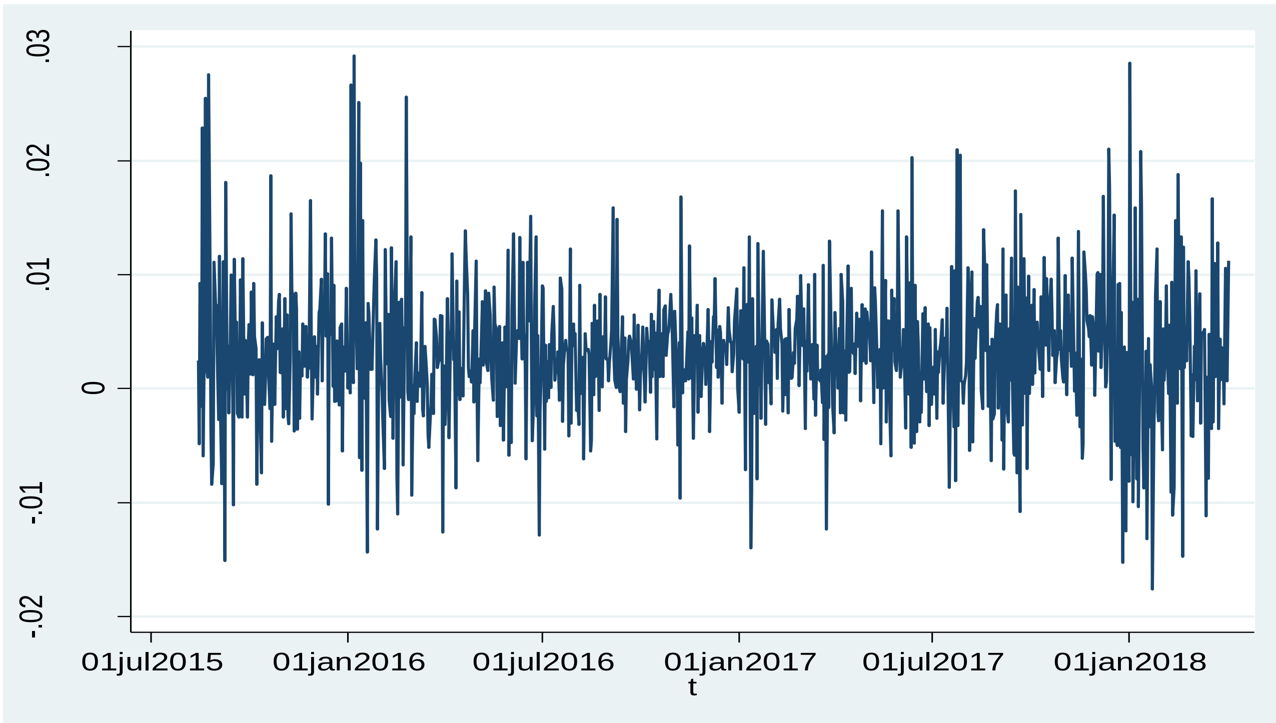
Table 9: White noise test for squared errors.

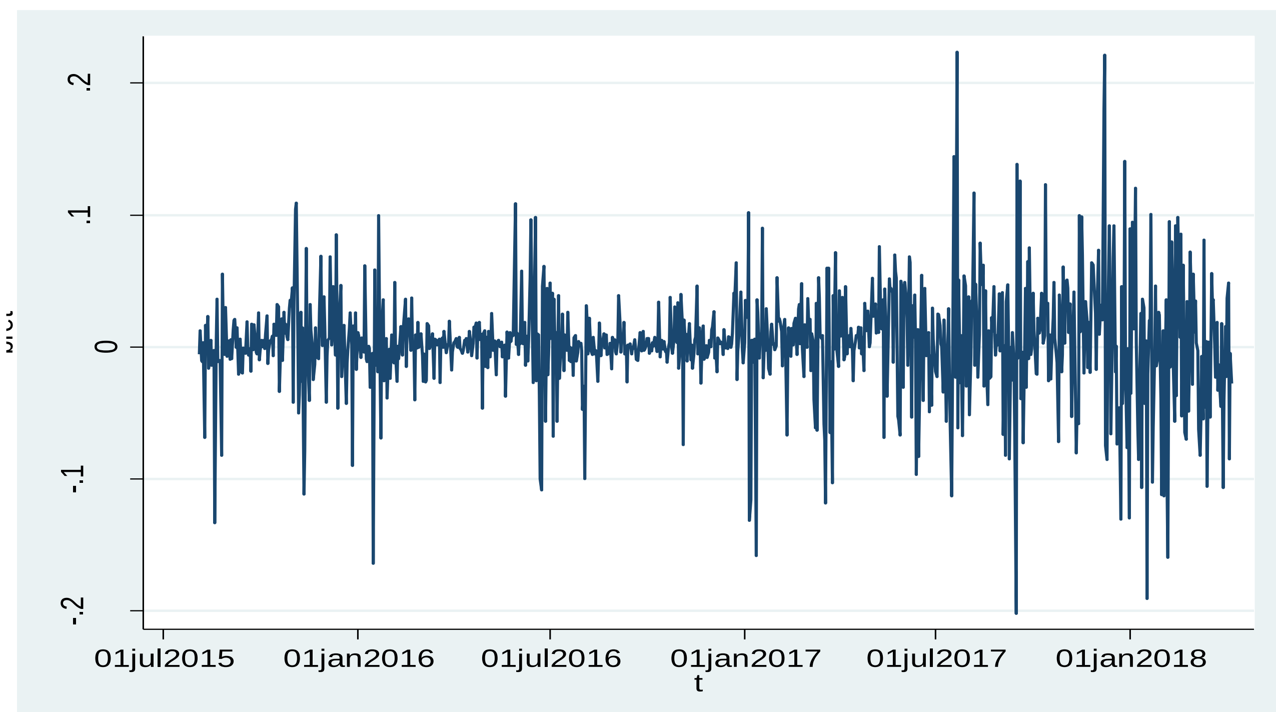
Portmanteau test for white noise

Portmanteau (Q) statistic	=	3.0484
Prob > chi2(7)	=	0.8805

We fail to reject that there is no serial correlation, meaning there is no autocorrelation. Now I predict the returns with this model. Here is the graph of predicted returns, together with the graph of actual returns. As we can see, predicted and actual returns have much in common. Although they have less magnitude, the areas of volatilities mostly coincide.

Figure 5: Predicted and realized Bitcoin price returns.





Now I will do exactly the same steps to make a model for Ethereum. As in the case with Bitcoin, the initial model with all variables included was a poor one, so I came up with a new one. The new model and the OLS regression results are given below.

$$eret = \beta_0 + \beta_1 eret_{t-19} + \beta_2 eret_{t-120} + \beta_3 sseret + \beta_4 vixret_{t-1} + \beta_5 uyret_{t-1} + \beta_6 cybret$$

Table 10: OLS of the model for eret.

Source	SS	df	MS
Model	.078973702	6	.013162284
Residual	4.3934691	944	.004654099
Total	4.4724428	950	.004707835

Number of obs =	951
F(6, 944) =	2.83
Prob > F =	0.0098
R-squared =	0.0177
Adj R-squared =	0.0114
Root MSE =	.06822

eret	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
eret						
L19.	.1034933	.0310006	3.34	0.001	.0426551	.1643314
L20.	.038352	.0264887	1.45	0.148	-.0136316	.0903356
vixret						
L1.	.0176143	.0309469	0.57	0.569	-.0431185	.078347
sseret	-.3614	.2235873	-1.62	0.106	-.8001857	.0773856
uyret						
L1.	-.005926	1.263379	-0.00	0.996	-2.485283	2.473431
cybret	.0141734	.0479658	0.30	0.768	-.0799586	.1083053
_cons	.0051886	.0022325	2.32	0.020	.0008073	.0095699

Afterwards, I run the Breusch-Godfrey test for autocorrelation.

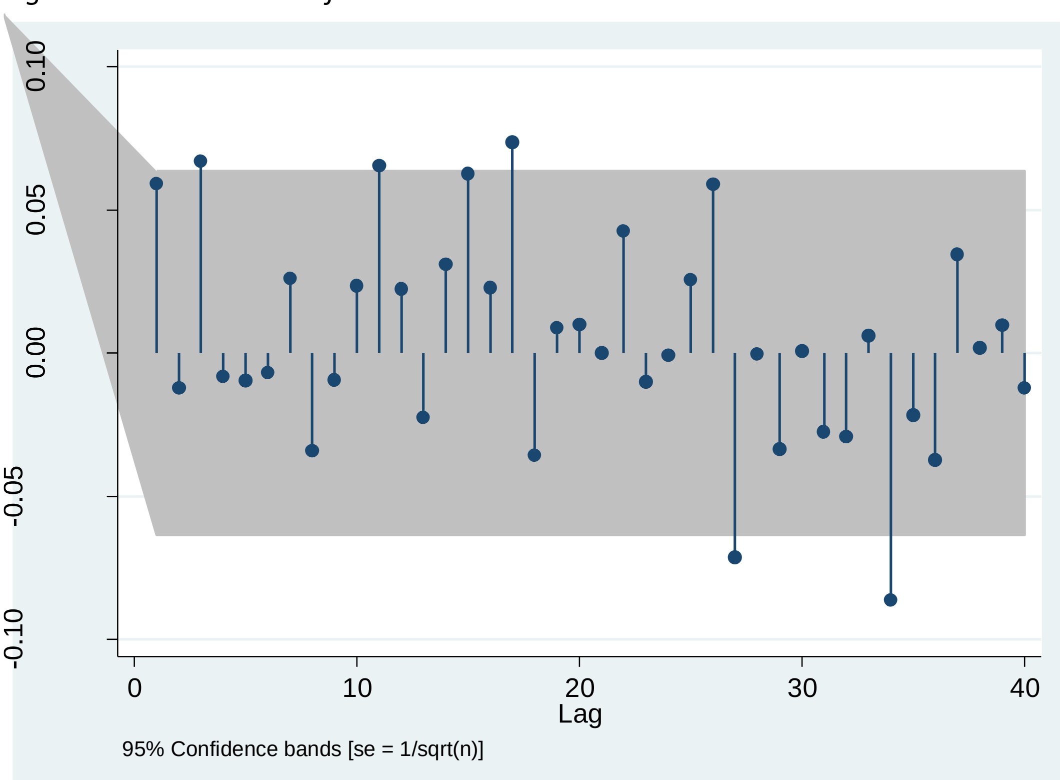
Table 11: Breusch-Godfrey LM test for autocorrelation of eret.

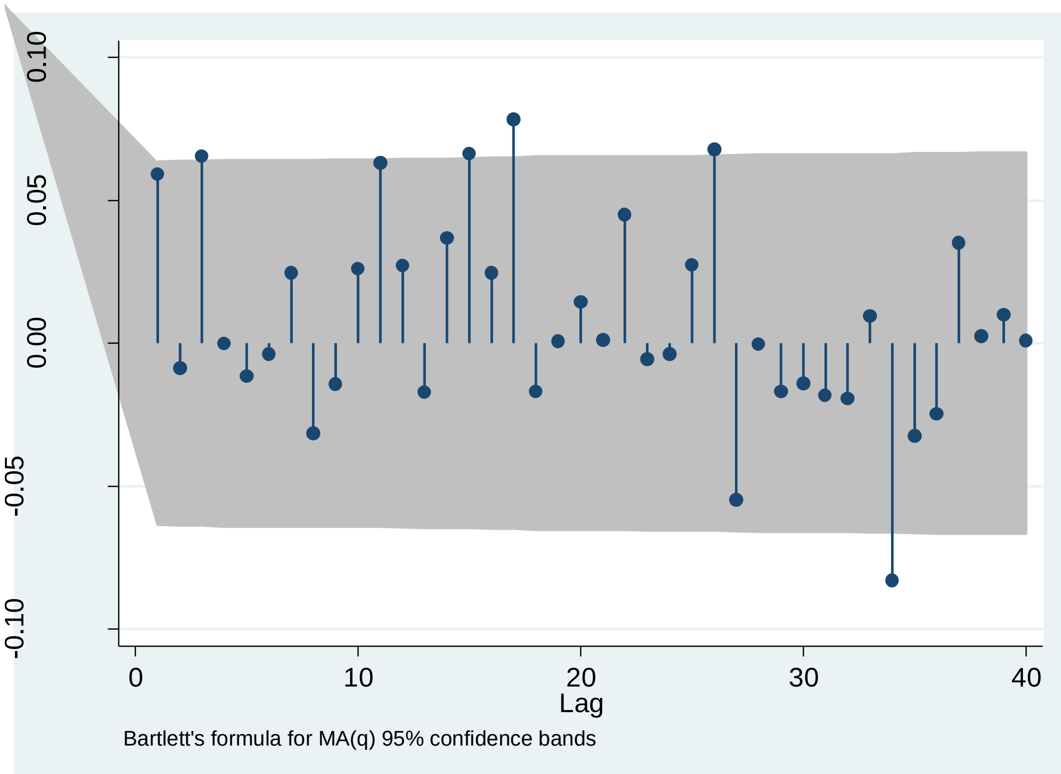
lags(p)	chi2	df	Prob > chi2
1	3.330	1	0.0680
2	3.472	2	0.1762
3	7.775	3	0.0509
4	7.840	4	0.0976
5	7.922	5	0.1606
6	7.966	6	0.2406
7	8.588	7	0.2836
8	9.704	8	0.2865
9	9.776	9	0.3689
10	10.306	10	0.4141
11	14.385	11	0.2124
12	14.845	12	0.2500
13	15.324	13	0.2876
14	16.242	14	0.2988
15	19.946	15	0.1740
16	20.431	16	0.2014
17	25.518	17	0.0837
18	26.692	18	0.0850
19	26.729	19	0.1111
20	27.196	20	0.1299
21	27.196	21	0.1645
22	28.777	22	0.1513
23	28.851	23	0.1853
24	28.852	24	0.2258
25	29.440	25	0.2460

H0: no serial correlation

As can be seen, there are several lags significant at 10%. Thus, there is an apparent need in ARMA model. Again, to determine the orders, I use PACF and ACF.

Figure 5: PACF and ACF of eret.





Here in both graphs the first lag is almost significant at 95% confidence interval, and is significant at 90%. Thus, the model chosen is ARMA (1, 1).

Table 12: ARIMA model for Ethereum price returns.

eret	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
eret						
eret						
L19.	.1052048	.029588	3.56	0.000	.0472133	.1631963
L20.	.038436	.0285718	1.35	0.179	-.0175638	.0944357
vixret						
L1.	.0154255	.030073	0.51	0.608	-.0435166	.0743676
sseret	-.3776853	.2139281	-1.77	0.077	-.7969767	.0416061
uyret						
L1.	-.1411746	1.360497	-0.10	0.917	-2.807699	2.52535
cybret	.0326031	.0459362	0.71	0.478	-.0574301	.1226363
_cons	.0051161	.0023972	2.13	0.033	.0004177	.0098146
ARMA						
ar						
L1.	-.7247943	.1528589	-4.74	0.000	-1.024392	-.4251963
ma						
L1.	.7799647	.1410407	5.53	0.000	.5035301	1.056399
/sigma	.0677579	.0010554	64.20	0.000	.0656894	.0698264

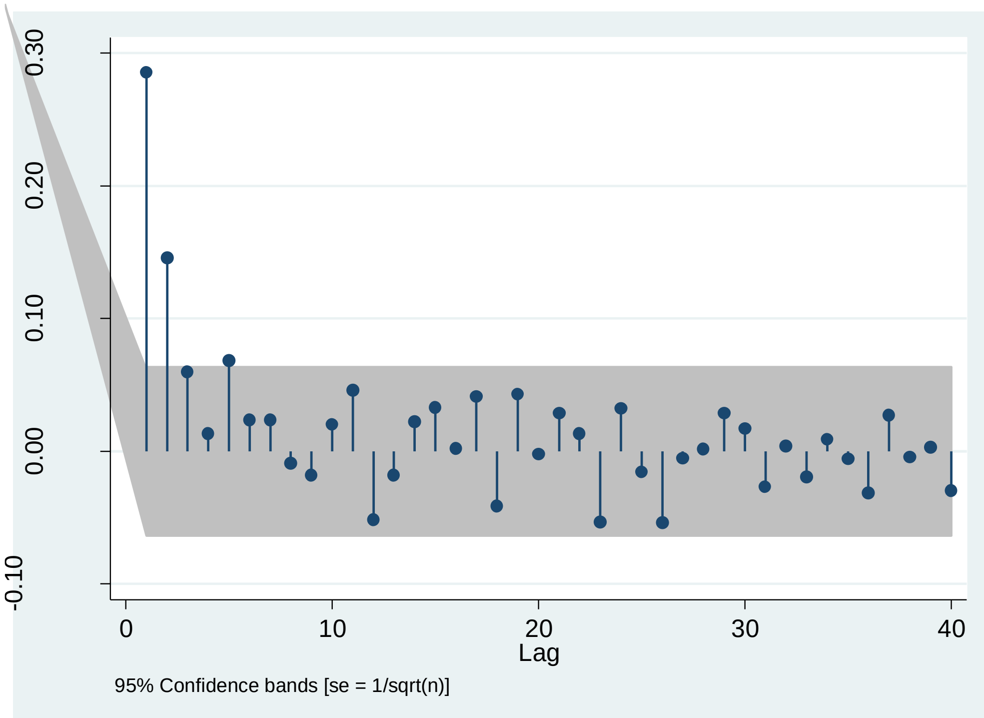
Further, I check for the fitted model using the Ljung-Box test. In other words I test for the white noise of the squared errors.

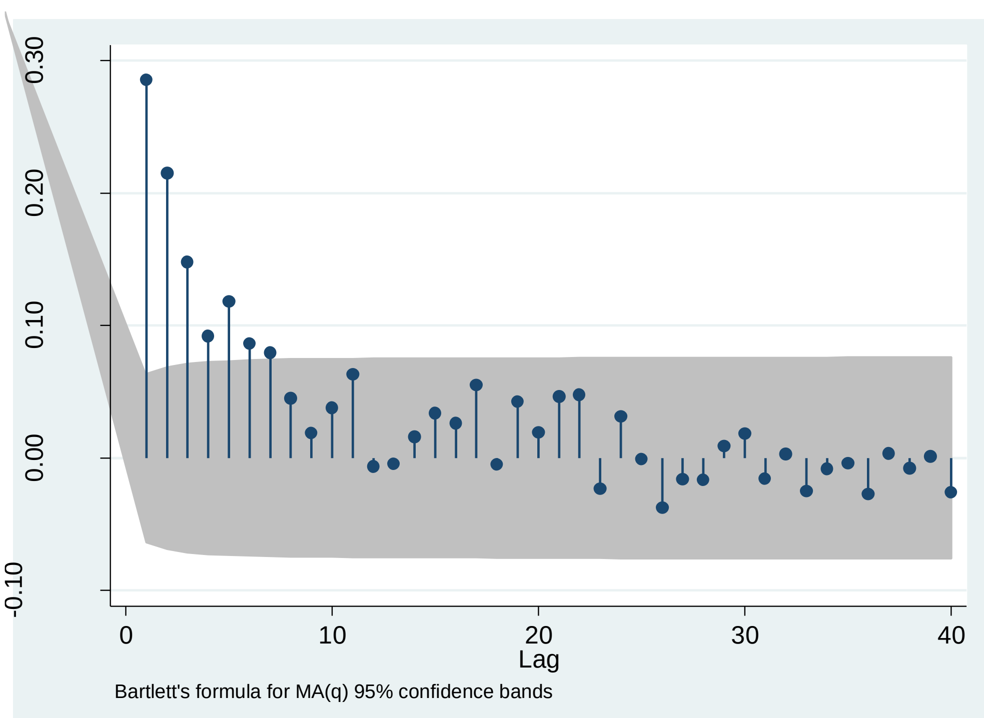
Table 13: Portmanteau test for white noise.

Portmanteau (Q) statistic	=	177.5082
Prob > chi2(7)	=	0.0000

The lag is again chosen by taking a natural log of n. The test suggests that there is an autocorrelation, and, consequently, an ARCH effect. Despite PACF and ACF suggesting taking GARCH (2, 7) model, I choose GARCH (1, 1), as it has much lower AIC and BIC. This may be explained by the fact that in both graphs the first graph is much more significant compared to the following lags.

Figure 6: PACF and ACF of squared residuals of the ARIMA model.





The resulting GARCH model is stationary, as the sum of coefficients does not exceed 1.

Table 14: AR-GARCH model for Ethereum price returns.

Sample: **28aug2015 - 04apr2018** Number of obs = **951**
Distribution: **Gaussian** Wald chi2(**8**) = **44.21**
Log likelihood = **1323.254** Prob > chi2 = **0.0000**

eret	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
eret						
eret						
L19.	.0800796	.0209982	3.81	0.000	.038924	.1212352
L20.	.0462769	.0206611	2.24	0.025	.0057818	.0867719
vixret						
L1.	.0402736	.0213978	1.88	0.060	-.0016654	.0822126
sseret	-.4352443	.1784612	-2.44	0.015	-.7850218	-.0854668
uyret						
L1.	-1.439862	.8274546	-1.74	0.082	-3.061643	.1819196
cybret	.0590214	.0301177	1.96	0.050	-8.22e-06	.1180509
_cons	.0024925	.0019089	1.31	0.192	-.0012488	.0062338
ARMA						
ar						
L1.	.4012549	.4916802	0.82	0.414	-.5624206	1.36493
ma						
L1.	-.3425975	.5069568	-0.68	0.499	-1.336214	.6510195
ARCH						
arch						
L1.	.2822797	.0313077	9.02	0.000	.2209177	.3436417
garch						
L1.	.707287	.0236149	29.95	0.000	.6610026	.7535714
_cons	.0002361	.0000415	5.69	0.000	.0001547	.0003175

This model is not a particularly good one, as ARMA coefficients are insignificant. I was able solve this by adding several variables to the variance equation. The variables are vix and usepeui at lag 10 and oil returns. Moreover, having the 19th and 20th lags of eret in the model is another refinement I came up to by numerous experimentations, and it significantly improves the overall model.

Table 15: A refined AR-GARCH model for Ethereum.

Sample: **28aug2015 - 04apr2018**	Number of obs	=	**951**
Distribution: **Gaussian**	Wald chi2(**8**)	=	**243.22**
Log likelihood = **1326.563**	Prob > chi2	=	**0.0000**

eret	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
eret						
eret						
L19.	.0695821	.0238204	2.92	0.003	.022895	.1162693
L20.	.053427	.0222208	2.40	0.016	.009875	.096979
vixret						
L1.	.0418113	.0222517	1.88	0.060	-.0018012	.0854238
sseret	-.4554969	.1796426	-2.54	0.011	-.8075899	-.1034039
uyret						
L1.	-1.62379	.8244379	-1.97	0.049	-3.239659	-.0079214
cybret	.054174	.0302281	1.79	0.073	-.005072	.11342
_cons	.002214	.0022916	0.97	0.334	-.0022776	.0067055
ARMA						
ar						
L1.	.9298129	.1092713	8.51	0.000	.7156451	1.143981
ma						
L1.	-.9110582	.1240522	-7.34	0.000	-1.154196	-.6679204
HET						
vix						
L10.	.0340048	.0186128	1.83	0.068	-.0024756	.0704851
usepui						
L10.	.0061254	.0020272	3.02	0.003	.0021521	.0100987
oilret	24.40389	7.185444	3.40	0.001	10.32068	38.4871
_cons	-9.426614	.3868852	-24.37	0.000	-10.18489	-8.668333
ARCH						
arch						
L1.	.270225	.0301195	8.97	0.000	.2111919	.3292581
garch						
L1.	.7057005	.0234456	30.10	0.000	.659748	.7516531

As the final step, I check the model for autocorrelation in errors. First, I calculate the standardized errors, and then run a White noise test on standard squared errors.

Table 16: White noise test for squared errors.

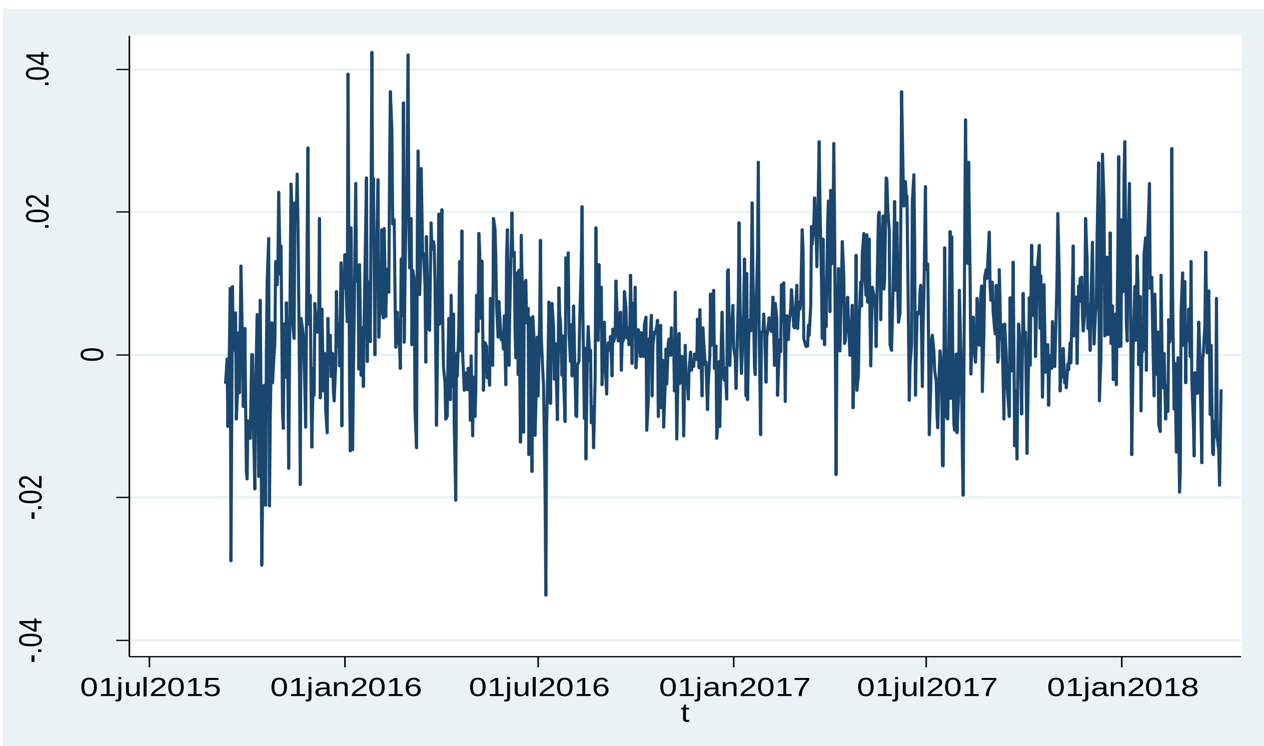
Portmanteau test for white noise

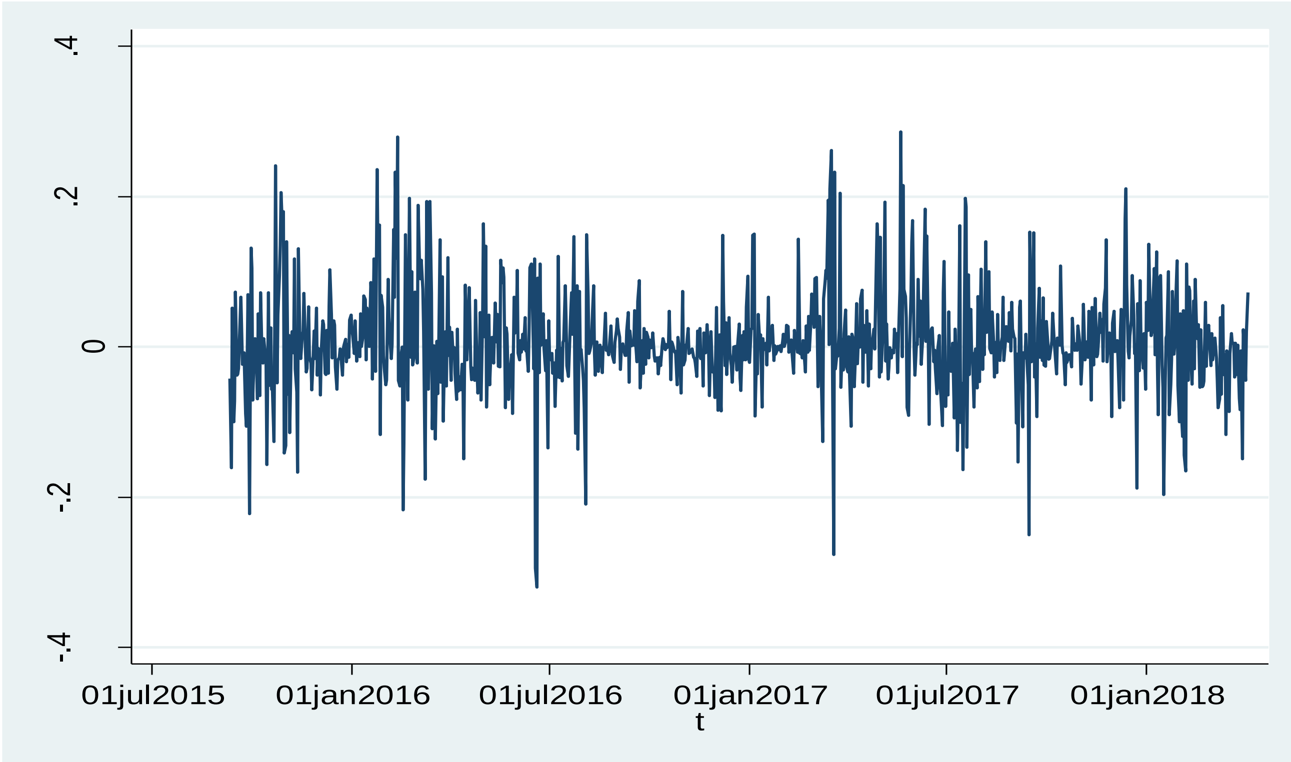
Portmanteau (Q) statistic	=	37.7131
Prob > chi2(40)	=	0.5737

We fail to reject that there is no serial correlation, which means the model fits well.

Now I can predict Ethereum returns.

Figure 7: Predicted and realized Ethereum price returns.





Results

The table below shows the final results for both models. First, a lagged increase in VIX is positively correlated with both cryptocurrencies. This makes sense, as when investors become more fearful about traditional financial assets they resort to alternatives like cryptocurrencies, driving their demand and prices up. For similar reasons, S&P and SSE indexes are negatively correlated, meaning when the companies perform poorly, BTC and ETH appreciate, possibly due to increased demand. It is noteworthy that Nikkei index is positively correlated, which may indicate that BTC is perceived as a more trusted traditional financial asset in Japan. Another reason can be an increase in online shopping, and especially imports, in Japan when its economy performs well, which drives up Bitcoin's prices, as it is widely used online. Moving forward, the USD/Yuan exchange rate is positively correlated with BTC. This means that when the Yuan appreciates, Chinese imports increase, and, as in the case with Japan, they are largely done online and often through BTC, which moves up its price. This also shows that BTC can be used in hedging against the dollar. Conversely, this exchange rate is negatively correlated with ETH. A possible explanation is that an increase in the rate means a depreciation for USD, which results in a reduction of money transfers done through ETH and reduces its prices. This may also mean that ETH is not used as much for online shopping as BTC. Gold returns have a positive coefficient for BTC, indicating that, much like gold, BTC is used for diversification and hedging. It is probably not the case for ETH though, as gold returns were insignificant for it. Oil returns are negatively correlated with BTC, possible indicating that, again, as the economy becomes more or less stable due to increases or decreases in oil prices, BTC prices move in the opposite direction, further showing its uses as a hedging tool. Another important finding is that both have Cyber 15 index returns significantly and positively correlated. This indicates that when cryptocurrency market performs well and appreciates, both of them move with the market. This is further supported by my observations of the market during the last 2 months. I have been checking the daily behavior of the top 50 cryptocurrencies, and, save for a couple of outliers, they all either were increasing or decreasing in their prices on a given day. Yet, it does not show if BTC follows the market, or the other way around.

Further, some ETH lags, chosen by ETH returns' PACF plot, show positive correlation. Both currencies show significant ARCH effects, meaning they have low convergence to long-term equilibrium, and persistent shock effects. The variance equation shows that oil returns' volatility significantly affects ETH returns' volatility, meaning that Ethereum's risk moves together with the panic caused by volatile oil prices. Finally, positive volatility shocks in VIX cause a decrease in BTC returns variance, which indicates that BTC is considered a safe asset, and an increase in ETH variance. Visual tests for predicting power of the models show that despite not being quite accurate, the models succeed in predicting the main volatility periods.

Conclusion

Introduced to the world in 2008, Bitcoin revolutionized the digital currency market. Having no intrinsic value, cryptocurrency market currently has a market capitalization of more than $300 billion. What made Bitcoin so popular are its deregulated nature, lack of necessity of a third party to verify transaction, relatively low transaction fees, and its speculative characteristics. Numerous cryptocurrencies emerged after the initial success of Bitcoin, the biggest of which after Bitcoin is Ethereum. Having practically the same technology behind them, they are far from being the same. This paper analyzed the impact of a number of macro-financial variables on Bitcoin’s and Ethereum’s prices. In spite of not being explained by a single model, there are some variables, like VIX, SSE index and Cyber15 index that are not only significant for both, but have the same signs. The results give some evidence that Bitcoin is also used for diversification and hedging, which is not observed for Ethereum. It would be useful to make similar models for more altcoins in the future, so as to have a better understanding behind the driving forces of the cryptocurrency market.

Table 17: GARCH models for Bitcoin and Ethereum.

Estimation Results

	BTC Coef./Se.	ETH Coef./Se.
main		
L10.vixret	0.0256**	
	(0.01)	
L.vixret		0.0418*
		(0.02)
nikret	0.2053***	
	(0.04)	
sseret	-0.2697***	-0.4555**
	(0.05)	(0.18)
spret	-0.2130**	
	(0.10)	
uyret	0.5278	
	(0.38)	
L4.cybret	0.0675**	
	(0.03)	
cybret		0.0542*
		(0.03)
L.goldret	0.1752**	
	(0.08)	
L5.oilret	-0.0490*	
	(0.03)	
L19.eret		0.0696***
		(0.02)
L20.eret		0.0534**
		(0.02)
L.uyret		-1.6238**
		(0.82)
Constant	0.0029***	0.0022
	(0.00)	(0.00)
ARMA		
L.ar	-0.5743*	0.9298***
	(0.31)	(0.11)
L.ma	0.6327**	-0.9111***
	(0.29)	(0.12)
HET		
L.VIX	-0.7555***	
	(0.07)	
L10.VIX		0.0340*
		(0.02)
L10.USEPUI	-0.0412***	0.0061***
	(0.01)	(0.00)
oilret		24.4039***
		(7.19)
Constant	1.6640	-9.4266***
	(1.03)	(0.39)
ARCH		
L.arch	0.1646***	0.2702***
	(0.01)	(0.03)
L.garch	0.8254***	0.7057***
	(0.01)	(0.02)
N	965.0000	951.0000
r2		
rmse		

Standard errors are in the parenthesis
* p<0.1, ** p<0.05, ***p<0.01

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Appendix

Table 18: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
bret	969	.0034591	.0407104	-.2020779	.2235126
eret	969	.0065929	.0714095	-.3198364	.4034572
spret	969	.0002323	.0070408	-.0425668	.038291
djret	969	.0003304	.0070093	-.0472212	.0387554
ftseret	969	.0000688	.007816	-.0481176	.0351496
sseret	969	-.0001846	.0111853	-.0892992	.0520172
nikret	969	.000041	.0114622	-.08253	.0742617
oilret	969	.0004025	.0203419	-.080822	.1128922
ueret	969	-.0001167	.0044565	-.0299526	.0243036
uyret	969	.0000158	.0018664	-.0118899	.0183818
cybret	969	.0028389	.0462638	-.1768456	.2785549
vixret	969	.0004251	.0740496	-.2998312	.7682452
puiret	969	.0010224	.5298743	-1.905441	2.602467

Table 19: Dickey-Fuller tests for all the variables

	Z	1%	5%	10%
bret	-30,526	-3,43	-2,86	-2,57
eret	-34,336	-3,43	-2,86	-2,57
spret	-32,056	-3,43	-2,86	-2,57
djret	-31,889	-3,43	-2,86	-2,57
sseret	-31,221	-3,43	-2,86	-2,57
nikret	-32,628	-3,43	-2,86	-2,57
ftseret	-32,371	-3,43	-2,86	-2,57
ueret	-31,913	-3,43	-2,86	-2,57
uyret	-28,856	-3,43	-2,86	-2,57
oilret	-31,703	-3,43	-2,86	-2,57
goldret	-31,912	-3,43	-2,86	-2,57
cybret	-29,677	-3,43	-2,86	-2,57
vixret	-32,068	-3,43	-2,86	-2,57
epuiret	-45,818	-3,43	-2,86	-2,57

Table 20: Preliminary results

	(1)	(2)
	eret	bret
main		
spret	1.499	-0.972
	(1.42)	(-1.90)
djret	-1.390	0.869
	(-1.35)	(1.69)
ftseret	0.253	0.0660
	(0.93)	(0.46)
sseret	-0.406*	-0.262***
	(-2.29)	(-4.62)
nikret	0.215	0.164*
	(1.17)	(2.14)
oilret	-0.0862	-0.0148
	(-0.92)	(-0.33)
ueret	-0.355	0.281
	(-0.74)	(1.42)
uyret	0.0293	0.324
	(0.02)	(0.70)
goldret	0.324	-0.00253
	(1.14)	(-0.02)
cybret	0.0557	-0.00687
	(1.21)	(-0.22)
vixret	0.0453	0.00438
puiret	0.00244	0.00278
	(0.63)	(1.51)
_cons	0.00198	0.00220**
	(1.08)	(2.79)
ARCH		
L6.arch	0.992***	
	(245.77)	
L.arch		0.165***
		(13.97)
L.garch	-0.00185	0.825***
	(-0.46)	(69.60)
_cons	0.00338***	0.0000247***
	(35.83)	(6.90)
N	971	975

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

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