Submitted: August 21, 2017

Title:

Bitcoin and Ethereum

- Hedging Capability and Potential for Bona Fide Money -

Advisor: Naoya SUEISHI

Student ID: 1402162E

Name: Yoshiki NAKAJIMA

Table of Contents

Introduction.. 1

1. Definitions and Concepts.. 3

1.1 Cryptocurrency.. 3

1.2 Bitcoin.. 4

1.3 Ethereum.. 5

1.4 Hedging Capability.. 6

1.5 Money... 6

2. Literature Review.. 8

3. Dataset... 11

4. Methodology... 13

5. Results... 17

6. Discussion and Conclusion... 27

References.. 30

Introduction

A cryptocurrency is a form of a digital asset which gained public attention with the rise of Bitcoin in late 2013. Bitcoin was first mentioned in 2008 by an anonymous cryptographer or a group of cryptographers who goes by the name Satoshi Nakamoto. This technology is characterized by what is called a peer-to-peer network, which allows transactions to be made between individuals without using intermediaries such as banks (Nakamoto, 2008). Since the introduction of Bitcoin, a number of digital currencies have been introduced, and there are more than 800 digital currencies in circulation with the total market capitalization of over a hundred billion dollars as of August 8, 2017, according to Coinmarketcap[i].

Cryptocurrencies are mostly considered in two ways: as an investment vehicle and as a currency. In the first purpose, users intend to accumulate returns in the expectation that the exchange rate goes up. As money, users see cryptocurrencies just like the fiat currency they use. In this paper, I analyze these two properties of cryptocurrency and investigate the hedging capability of cryptocurrency for an investment and the potential to function as a bona fide currency alongside traditional money.

The result of the AR and GARCH analysis showed that Bitcoin and Ethereum have characteristics of a hedge against market risk as an investment and shares some features with gold. As a currency, they do not function as money by now, but the historical trend shows cryptocurrencies, especially Bitcoin, are becoming to satisfy the criteria of money. Also, the differences of Bitcoin and Ethereum have found. These include the primary purpose of their protocol, some supply side factors, and the speed of which they become a bona fide currency.

The previous studies about digital money's properties are mainly about Bitcoin because it amounted most of the market cap. However, the recent development of cryptocurrencies has increased the share of other digital currencies, especially Ethereum.

---

[i] https://coinmarketcap.com/ (Accessed on August 8, 2017)

This paper intends to supplement the lack of the studies into Alt-coins, digital money other than Bitcoin, by providing an investigation into Ethereum and the comparison of the two biggest digital currencies.

A cryptocurrency, especially the one with a distributed ledger, is an entirely new idea of a transaction. The technology can be applied not only to the financial industries but also to everywhere an exchange takes place. This is why the technology is also called "the internet of money." The Internet made information available to everyone who has access to the technology. Just like that, cryptocurrencies (technically speaking it is the blockchain, the underlying technology behind the cryptocurrency) have the potential to distribute one's value freely without any interventions by a third-party. He or she just needs to have access to the network. It is worth exploring and identifying the properties of the technology and getting the implications for the future economy, considering the potential of this technology altering and disrupting the conventional way in which business and the economy works.

The remainder of this paper is structured as follows. After this introduction, the definitions, basic concepts and theoretical explanations are given in Section 1. Section 2 contains the overview of the past studies. The dataset for the analysis is presented in Section 3. Section 4 covers the econometric background and methodology implemented. Section 5 shows the result and interprets it, and Section 6 discusses and concludes the findings of this study.

1. Definitions and concepts

1.1. Cryptocurrency

Cryptocurrency is a currency in a digital form based on cryptography. Committee on Payments and Market Infrastructures, a board of the Bank for International Settlements, identified three distinctive characteristics in this scheme (CPMI, 2015). The first aspect is that it is an asset in which the supply and demand determine the value, which is intrinsically zero and relies only on the belief (see more for *1.5: money*).

Another feature is the way it transfers value within its network. Some of the digital currencies use the scheme called the distributed ledger that allows the exchanges of electronic value to happen between a payer and payee without the need for intermediaries. In the traditional system, the peer-to-peer exchange was only possible when two parties are physically present. If someone wants to transfer his or her value remotely, he or she needs to rely on the trusted third party such as banks to execute a transaction. In the absence of a middle person, there is a risk that the transaction history is changed, so people make transactions via trusted intermediaries that own centralized ledger with information on transaction history. This system of trust has facilitated the transactions by avoiding the risk but makes the operation somewhat expensive because of the fee for intermediaries.

The distributed lodger is the system that doesn't require intermediaries without losing the security of operations. Under this scheme, a transaction history is divided into small chronological pieces called "blocks," copied and distributed across the network. This makes the changing of history almost impossible because it requires altering all the information within blocks that are scattered around the system. This makes a cryptocurrency innovative not only from an asset point of view but also from a payment mechanism perspective. For example in the case of US dollar or Japanese yen, it is, of course, currency, but it does not refer to a system of payment. Visa or PayPal is a payment method, but they do not have their currency. The digital currencies using distributed ledger have the ability to achieve both at the same time, which may disrupt the existing business model.

The third distinguishing feature is the institutional arrangements. In most of the digital currency schemes, there are no particular responsible individual or institution such as network operators or vendors. Some intermediaries exist such as exchanges, but they are not essential for the scheme, or substitutable. Instead, computer protocols are responsible for how the system works, and different currencies have a different policy over each mechanism.

These are three of the characteristics of digital currencies but not a prerequisite. In this paper, I focus on two of the most widely used cryptocurrencies that satisfy all above features and cover around 70% of market capitalization in digital currency market: Bitcoin and Ethereum. The following subsections explain the similarity and differences of them.

1.2 Bitcoin

Bitcoin is the very first cryptocurrency with three features mentioned above. The original idea was introduced in 2008 by Satoshi Nakamoto, whose identity remains unknown until now. The unit is called a bitcoin or BTC in short. Currently, 16 million bitcoins are in circulation with the maximum amount of 21 million. The amount of supply halves approximately every four years until 2140 when all bitcoins are "mined," or supplied. This makes Bitcoin a deflationary, scarce asset like gold. Since a confirmation of a block is a necessary for distributed ledger scheme and this work is compensated by the issuance of new currency, it is an open question whether the scheme is sustainable after a new supply becomes zero or almost zero. However, some experts such as Fred Ehrsam, a co-founder of Coinbase, one of the biggest cryptocurrency exchanges in the world, point out the possibility of the change of the protocol by an agreement by the majority of those involved in the confirmation process called "miners" (Goldman Sachs, 2016). The size of a "block," on which distributed ledgers are based, is 1MB. Since one block is approximately 10-minute long, the theoretical number of transactions per second is limited to seven at maximum[ii] (Vukoilc, 2015). This is causing a problem as Bitcoin gains popularity, and more people use it for transactions. Indeed, a Bitcoin transaction now costs an average fee of $ 0.62 per transaction because of the congestion of the network (Coindesk, 2017). This scalability problem is one of the biggest impediments for Bitcoin as a payment mechanism, compared to traditional ones such as VISA, whose network is capable of handling 56,000 transactions per second[iii]. This paper follows the convention of the denotation Bitcoin, capitalized, to refer to the system, the software and the network it runs on it, and bitcoin, with lower-b to refer to the currency itself.

1.3 Ethereum

Ethereum is an application platform based on a built-in cryptocurrency called ether (ETH). Ethereum, therefore, has more developing opportunities than Bitcoin has, such as a smart contract. A smart contract is a contract written in a cryptographic code and designed to work in a way defined beforehand. For example, someone wants to buy a house from another he/she does not know, hence not trustworthy. In the traditional system, intermediaries such as real estate agents are needed to avoid the violation of the agreement such as a dual contract. A smart contract includes conditions, for example, if a payment of 100 ethers has made, the owner has to pass the key to the contractor. However, if the buyer does not make a payment or the owner does not yield the property, the contract is declared void, and the balance of ether is the same as the beginning. Therefore, unlike Bitcoin, which may affect the whole financial market

[ii] On August 1, Bitcoin split into the two over the size of the block. A hard fork created a new currency called Bitcoin Cash (BCC/BCH), which has a block size of 8MB. The original Bitcoin is expected to increase its block size to 2MB in November. In this paper, however, I don't analyze this issue because the investigation period does not include this fork. See more at: https://www.coindesk.com/full-steam-ahead-segwit2x-reconfirm-bitcoin-hard-fork-plan/ (accessed on August 16, 2017)

[iii] https://usa.visa.com/dam/VCOM/download/corporate/media/visa-fact-sheet-Jun2015.pdf (accessed on August 16, 2017)

infrastructures, Ethereum can change the entire system of economy where a value is transferred from one person to another. This is another significant innovation of distributed ledger with a potentially huge impact on how the business is working in today's economy.

In Ethereum, there is no predetermined amount of supply by its protocol. It is increasing at a constant rate, and 94 million ethers are currently in circulation. Five ethers are added every time a block is confirmed. The confirmation time of each block is approximately from 10 to 12 seconds, and roughly 15 transactions are processable per second. This amount is more than the double in scale compared to Bitcoin, but still be very small in comparison to the existing systems like VISA. A serious delay in the confirmation has yet to be seen because of the lack of an absolute number of users who want to exchange goods or services using ether, or willing to have a smart contract via Ethereum network. Thanks to this, the average transaction cost is \$ 0.02-0.03 per a transaction (Coindesk, 2017; Hertig, 2016)

1.4 Hedging capability

A hedge is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio on average (Baur and Lucey, 2010). Having an asset with a hedging capability in the portfolio can diversify the risk of investment because the loss from one asset may be offset by another asset with hedging capacity. The definition does not include the negative or non-correlation in times of market stress or crisis. This kind of property is called a safe haven asset.

1.5. Money

Traditional money can be classified into two types depending on whether it has an intrinsic value: Fiat money and commodity money. The money that is widely used in today's economy, such as US dollar or Japanese Yen, belongs to the first category. They do not have intrinsic value because they are just papers, but are valued more thanks to a government decree, or fiat. The other type of money is called commodity money. This kind of money has some intrinsic value and is used to be the norm before fiat currency is commonly accepted. The most widespread example of this is gold. When people use gold as money, the economy is said to be on a gold standard and was common during the late nineteenth century (Mankiw, 2015). Cryptocurrency belongs to neither of the two. Unlike commodity money, cryptocurrency does not have intrinsic value because it is just a digital token after all. However, it is not a fiat currency either because there is no decree issued by a government to support it.

Another perspective to look at money is its function. Money has three purposes that define it: Medium of exchange, Unit of account and store of value. A medium of exchange refers to the ability of money to trade goods or services with ease. This easiness is called liquidity. Unit of accounts means that money provides the terms in which prices are quoted and debts are recorded. Finally, as a store of value, money is a way to transfer purchasing power from the present to the future (Mankiw, 2015).

2. Literature Review

A number of studies about cryptocurrencies, most of which are about Bitcoin, can be divided into two broad categories. The first group considers the general and theoretical aspects of cryptocurrencies such as Dwyer (2015) that investigated the factors affecting digital currencies' price equilibrium and volatility. This group includes studies regarding the classification of cryptocurrencies as a currency or as an asset. Bitcoin initially started as a monetary system, as the title of the paper by Nakamoto (2008) call it "a peer-to-peer electronic cash system." However, because of the shared characteristics of gold, it is often referred to as an asset. Glaser et al. (2014) focused on users' intentions when they bought bitcoins and investigated whether users see this new form of digital currency as a currency or as an asset. The result of their ARCH model analysis showed that new users with limited knowledge about Bitcoin tend to see it as an investment vehicle and do not have much interest in its currency aspect. Dyhrberg (2016a) compared bitcoins with gold and US dollar. The similarities of cryptocurrencies to gold have long been discussed because they share various characteristics. For instance, both don't have any governments that control the amount of supply, and the law of supply and demand determines the price, which is way above their intrinsic value. Also, both are scarce goods, and the amount of supply diminishes over time. Note that the discussion of overvaluation can also be applied to a fiat currency that has almost no intrinsic value and government can get seigniorage. The scarcity and diminishing supply is the case for Bitcoin, not for Ethereum. Dyhrberg implemented GARCH model analysis and found Bitcoin's similarities both to the US dollar and gold, therefore concluding Bitcoin's position as "somewhere in between a currency and a commodity."

Yermack (2013) and Cermak (2017) discussed whether Bitcoin could function as a bona fide currency. Both papers analyzed whether Bitcoin satisfies each of the three criteria for money: medium of exchange, unit of account and store of value. In short, even Bitcoin, the most famous cryptocurrency, doesn't satisfy any of currency criteria. Both Yermack and Cermak blame one common factor for preventing each criterion from being satisfied: volatility. If the price fluctuates largely, it will disincentivize merchants to accept the currency because of the potential loss from depreciation, hence less function as a medium of exchange. It also imposes the cost of adjusting the price in accordance with the fluctuation if it acts as a unit of account. Besides, store of value requires the price to be stable because the worth has to be kept unchanged. A number of other researches also supports this insufficiency as a currency. Hill (2014) showed the difficulty to use a bitcoin as a medium of exchange by experimenting living a week only out of bitcoin. Vorick (2017) points out the lack of fungibility in bitcoin. This means that one bitcoin that one person has may be more or less valuable than one bitcoin that another person has. The exchanges are not willing to receive a bitcoin if that is likely to be the one stolen or the one used for criminal activity such as money laundering.

The second group of the literature studied the quantitative and practical aspect of cryptocurrencies. Brandvold et al. (2015) investigated the role of bitcoin exchanges in the price discovery process. They found some of the bitcoin's trading platforms with large volume acted as price leaders while others following the trend as price takers. Dyhrberg (2016b) implemented the GARCH model analysis to find the factors influencing bitcoin's price and its volatility, using FTSE index and dollar exchange rate with the Euro and Sterling as explanatory variables. The result showed no significant correlation with FTSE and a small positive correlation with US dollar, indicating the hedging capability of bitcoin. Szetela et al. (2016) identified the relation between major exchange rates and the price of bitcoin. They applied ARMA-GARCH model analysis and found no correlations between the price and the exchange rates while showing the significant correlation of the volatility with the US Dollar, Euro, and Yuan, which indicates the dependency of bitcoin on some of the major economies in terms of the volatility. Yermack investigated the correlation of bitcoin price to some of the exchange rates and the price of gold and found no significance, indicating the independent movement of bitcoin price. He also found a significant correlation between bitcoin price and the stock price of the Vitamin Shoppe, the US-based retailer, in the 2011-12 period[iv].

[iv]. However, the separate regression was run using the dataset of 2016-17 and showed no significance. Considering the small market cap of the Vitamin Shoppe their nonacceptance of any cryptocurrencies, the

Cermak (2017) investigated the influence of stock index, bond rate and interbank rate of US, EU, China and Japan over the price and volatility of bitcoin. The results indicated no variables considered are significant to explain the change in the price of bitcoin. Regarding the volatility he found that the macroeconomic variables of US, Euro, and China have an effect but the variables of Japan do not have an influence because of the limited trading volume. He also found that historical trend of volatility is decreasing, and bitcoin achieves volatility level as low as fiat currency by 2020 if this trend continues.

---

correlation found can be concluded as a coincidence. The result of the analysis is omitted but available upon request.

3. Dataset

Bitcoin price data is sourced from Bitcoin Price Index (BPI) provided by Coindesk[v]. The observation period covers from July 19, 2010, to June 30, 2017. BPI is the price index of a bitcoin, denominated in US dollar and is an average of the world's large bitcoin exchanges. I use this index in the analysis because the differences exist of the price of a bitcoin amongst the exchanges. The daily price data of Ethereum is retrieved from Etherscan[vi] and covers from August 1, 2015, to June 30, 2017. This is almost the entire period since the system went live on July 30, 2015. Figure 1 and Figure 2 show the movements of the price of bitcoin and ether during the period considered.

Also collected were S&P500, STOXX50, NIKKEI225, USD/EUR exchange rate, USD/JPY rate, Federal Fund rate and Gold price in London Bullion market. These are the explanatory variables for the regression model that is introduced in Section 5. The explanatory variables were selected based on the studies by Tully and Lucey (2007) in the analysis of gold, and Dyhrberg (2016b) and Cermak (2017), of Bitcoin. The data was sourced from New York Fed[vii] for the daily effective Federal Fund rate, and Federal Reserve Economic Data (FRED) provided by Saint. Luis Fed[viii] for the other explanatory variables. Table 1 shows the summary statistics.

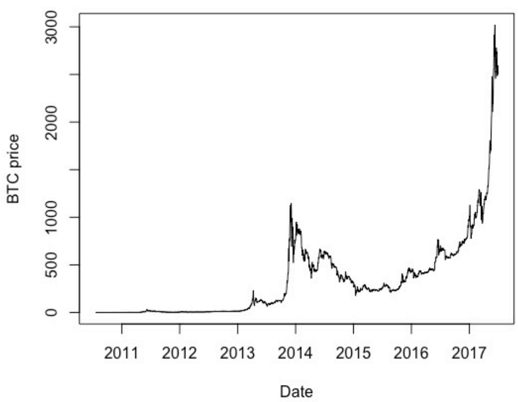

Figure 1: Price of Bitcion

[v] https://www.coindesk.com/ (Accessed on July 4, 2017)
[vi] https://etherscan.io/chart/etherprice (Accessed on July 10, 2017)
[vii] https://www.newyorkfed.org/ (Accessed on July 4, 2017)
[viii] https://www.stlouisfed.org/ (Accessed on July 4, 2017)

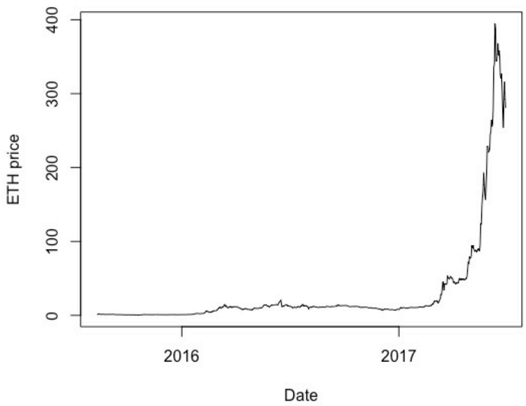

Figure 2: Price of Ether

Variables	N	Mean	SD	Min	Max
BTC Price	2539	331.3	438.0	0.05	3018.5
ETH Price	690	28.9	65.8	0.43	394.7
SP500	1752	1737	382.1	1047	2453
STOXX50	1668	2912	387.6	1995	3829
NIKKEI225	1706	14043	4017.9	8160	20868
GOLD	1757	1371	198.7	1051	1896
USD/EUR	1744	0.81	0.080	0.67	0.96
USD/JPY	1744	98.8	15.5	75.7	125.6
FF rate	1741	0.21	0.206	0.04	1.16

Table 1: Summary Statistics

4. Methodology

In most of the time-series analysis, it is assumed that a time-series data is covariance-stationary or weakly stationary. In other words, neither the mean μ_t nor the autocovariance γ_{jt} depends on the date t. (Hamilton, 1996). The conditions can be described as follows:

$$E(Y_t) = \mu \tag{1}$$

$$E(Y_t - \mu)(Y_{t-j} - \mu) = \gamma_j \tag{2}$$

for all *t* and any *j*, where:

$Y_t\ is\ an\ observed\ sample\ of\ T\ of\ some\ random\ variables, \{y_1, y_2, \ \dots, y_t\}$

Dickey-Fuller test is a statistical test to examine if a time-series data discussed is stationary (Dickey and Fuller, 1979). The null hypothesis is that a time-series has a unit root. The alternative hypothesis is that the data is stationary. When the result of Dickey-Fuller test is not rejected, which often happens in financial time series data, log returns are typically used to reach the stationarity. Log returns are defined as the first difference of the natural logarithm of the price. This is described as,

$$r_t = ln(P_t) - ln(P_{t-1}) \tag{3}$$

where:

r_t: log returns at time *t*

P_t: price at time *t*

This log return can be approximated to a simple return when rate of return is small[ix]. That is,

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \approx ln(P_t) - ln(P_{t-1}) = r_t \tag{4}$$

where:

R_t = simple returns at time t

---

ix For further mathematical details, see Hamilton (1994), pp. 711-721

Once the data is transformed into a stationary data, ARMA (p, q) process is applied. ARMA stands for AutoRegressive Moving Average and is a combination of two models; the autoregressive model of order p and the moving average model of order q. The autoregressive process of order p means the value at time t depends on p previous observations and the white noise at time t. Which is written as follows:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t \qquad (5)$$

where:

c: constant

ε_t: white noise, i.e., $E(\varepsilon_t) = 0$, $V(\varepsilon_t) = \sigma^2$ and $cov(\varepsilon_t, \varepsilon_{t+j}) = 0$

$\{\phi_1, \dots, \phi_p\}$: parameters

When the value at time t depends on q previous random terms, it is called the moving average of order q, written as:

$$y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_p \varepsilon_{t-p} \qquad (6)$$

where:

μ: constant

$\{\theta_1, \dots, \theta_p\}$: parameters

The ARMA(p, q) model is a combination of the autoregressive process of order p and the moving average process of order q, which can be described in the following form:

$$\begin{aligned} y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t \\ + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \end{aligned} \qquad (7)$$

It is important to note that the models mentioned above are based on the assumption of constant conditional variance at time t, i.e., $V(\varepsilon_t|\Omega_{t-1}) = \sigma^2$, where Ω_{t-1} $is\ the\ information\ set\ till\ time$ $\mathrm{t}-1$. However, financial time series data often fails to meet this assumption, which is called heteroskedasticity. Engle (1982) introduced the ARCH model, which stands for Autoregressive Conditional Heteroskedasticity to estimate the time series data with volatility clustering, namely, an observation with high volatility is followed by another observation with high volatility and vice versa. The ARCH process of order p is an application of the autoregressive process of order p to the square of the disturbance term. The model can be described in the following forms:

$$r_t = \mu_t + \varepsilon_t \tag{8}$$

$$\varepsilon_t = \sigma_t v_t \tag{9}$$

$$v_t \sim N(0,1) \tag{10}$$

$$E[\varepsilon_t^2 | \Omega_{t-1}] = \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{11}$$

where:

μ_t is a conditional mean at time t, or $E[r_t | \Omega_{t-1}]$

$\omega \geq 0$ and $\alpha_j \geq 0$ to ensure positive variance.

Ω_{t-1} is an information set till *t-1*, or $\{r_1, r_2, \dots, r_{t-1}\}$

μ_t is a constant but can be replaced by a time series model such as AR, MA or ARMA. In order to investigate whether heteroskedasticity exists, Engle (1982) also developed a statistical test, called Lagrange Multiplier test for the ARCH. Let e_t a vector of residuals, described as:

$$e_t = r_t - \widehat{\mu_t} \tag{12}$$

The auxiliary regression is constructed under lag order of p, i.e.,

$$e_t^2 = \alpha_0 + \alpha_1 e_{t_1}^2 + \alpha_2 e_{t-2}^2 + \dots + \alpha_p e_{t-p}^2 + u_t \tag{13}$$

where:

$\{\alpha_0, \dots, \alpha_p\}$: parameters

u_t: white noise.

The null hypothesis is no ARCH effect, described as:

$$H_0: \alpha_1 = \alpha_2 = \dots = \alpha_p = 0 \tag{14}$$

The alternative hypothesis is non-zero parameter α, which indicates the time-dependency of residuals. The test statistics are computed by TR^2, where T is the sample size in the auxiliary regression, and R^2 is the coefficient of determination for the auxiliary regression. Under the null hypothesis, the test statistic follows $a\,\chi^2$ distribution with p degrees of freedom.

The problem of the ARCH model is that the order tends to be larger and the interpretation becomes complex when volatility lasts long, which is often seen in financial time series data (Okimoto, 2010). Bollerslev (1986) introduced an extension of ARCH model called the GARCH model, or Generalized Autoregressive Conditional Heteroskedasticity. The GARCH model, therefore, allows for a more flexible lag structure with fewer parameters. The GARCH model is written in the following forms:

$$r_t = \mu_t + \varepsilon_t \tag{15}$$

$$\varepsilon_t = \sigma_t v_t \tag{16}$$

$$v_t \sim N(0,1) \tag{17}$$

$$E[\varepsilon_t^2 | \Omega_{t-1}] = \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{18}$$

The ARCH and GARCH models have been expanded since, for example, the integrated GARCH (IGARCH) to allow for permanent volatility, the threshold ARCH (TARCH) and the exponential GARCH for an asymmetric impact of innovations. The detailed discussion on the specification of the ARCH-type models can be found in Hansen and Lunde (2005). GARCH (1,1) model is the most commonly used model in the empirical study of financial time series data. Indeed, this model is used by Cermak (2017) and Dyhrberg (2016a) for bitcoin analyses, and Capie et al. (2005) and Tully et al. (2007) for gold analyses, and so forth. In this paper, I therefore use GARCH (1,1) model.

5. Results

The primary focus of this analysis is to examine the hedging capability of Bitcoin and Ethereum as an asset and the potential to function as money. This section consists of three parts in which I preprocess the data, investigate the asset properties, and monetary side of Bitcoin and Ethereum.

To implement the model introduced in Section 4, first, the data need to be prepared stationary. As seen in Figure 1 and 2 in Section 3, the price of bitcoin and ether seem to be nonstationary. Augmented Dickey Fuller test is performed to validate this, and the result leads us to accept the null hypothesis of the unit root (Table 2).

Augmented Dickey-Fuller Test		
Variable	Dickey-Fuller	P-value
Bitcoin Price	1.3657	0.99
Ethereum Price	-0.93533	0.949

Table 2: ADF test for BTC/ETH price

Then, the log returns are computed to reach stationarity. The results of ADF test for the log return of the prices reject the null hypothesis, leading to the alternative hypothesis of stationarity (Table 3). The return data is plotted in Figure 3 and Figure 4.

Augmented Dickey Fuller Test		
Variable	Dickey Fuller	P-value
Bitcoin Return	-16.741	0.01*
Ethereum Return	-8.7228	0.01*

**p-value smaller than printed p-value*

Table 3: ADF test for BTC/ETH log return

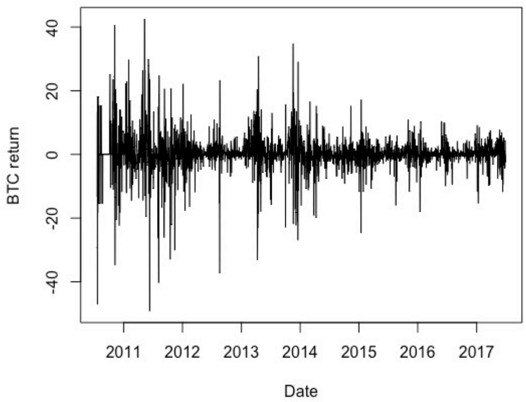

Figure 3: log return of Bitcoin

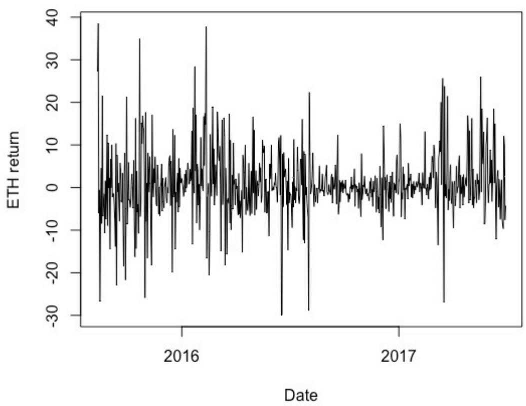

Figure 4: log return of Ether

The same processes are implemented for the explanatory variables as well. Unit root is found for all the explanatory variables except Federal Fund Rate, and first differencing of natural logarithm negate unit root to reach the stationarity. The details are in Table 4.

Therefore, I will use log return data for all the variables except Federal Fund rate. Summary statistics of the transformed dataset are in Table 5.

Augmented Dickey Fuller Test		
Variables	Dickey Fuller	P-value
SP500	-2.8404	0.2226
STOXX50	-2.502	0.3658
NIKKEI225	-2.2451	0.4745
GOLD	-2.8435	0.2212
USD/EUR	-2.4682	0.3808
USD/JPY	-1.7335	0.6911
FF rate	-4.8136	0.01*
ΔlnSP500	-18.682	0.01*
ΔlnSTOXX50	-17.233	0.01*
ΔlnNIKKEI225	-17.307	0.01*
ΔlnGOLD	-16.575	0.01*
ΔlnUSD/EUR	-16.476	0.01*
ΔlnUSD/JPY	-16.7	0.01*

**p-value smaller than printed p-value*

Table 4: ADF test for explanatory variables

Variables	N	Mean	SD	Min	Max
BTC return	2538	0.4078	5.89	-49.1528	42.4579
ETH return	689	0.8196	7.87	-29.9228	38.4739
ΔlnSP500	1751	0.0436	0.926	-6.8958	4.6317
ΔlnSTOXX50	1667	0.0125	1.341	-9.0110	5.8978
ΔlnNIKKEI225	1705	0.0505	1.376	-11.1534	7.4262
ΔlnGOLD	1756	-0.0062	1.028	-8.9128	4.7883
ΔlnUSD/EUR	1743	0.0028	0.586	-3.0643	2.6724
ΔlnUSD/EUR	1743	0.0119	0.617	-3.4977	3.3428
FF rate	1741	0.2117	0.206	0.0400	1.1600

Note: ΔlnX $denotes\ the\ first\ difference\ of\ natural\ logarithm\ of\ X$

Table 5: Summary statistics of the data transformed

Then, two separate AR (1) models are formed to investigate the correlation of the macroeconomic variables of major economies and a previous term's return, to the return of bitcoin and ether, respectively. The models are described as follows:

$$\begin{aligned} BTC\ return_t = {} & \beta_0 + \beta_1 BTC\ return_{t-1} + \beta_2 \Delta lnSP500_t \\ & + \beta_3 \Delta lnSTOXX50_t + \beta_4 \Delta lnNIKKEI225_t \\ & + \beta_5 \Delta lnGOLD + \beta_6 \Delta ln\mathrm{USD/EUR}_t \\ & + \beta_7 \Delta ln\mathrm{USD/JPY}_t + \beta_8 FFrate_t + \varepsilon_t \end{aligned} \tag{19}$$

$$\begin{aligned} ETH\ return_t = {} & \beta_0 + \beta_1 ETH\ return_{t-1} + \beta_2 \Delta lnSP500_t \\ & + \beta_3 \Delta lnSTOXX50_t + \beta_4 \Delta lnNIKKEI225_t \\ & + \beta_5 \Delta lnGOLD + \beta_6 \Delta ln\mathrm{USD/EUR}_t \\ & + \beta_7 \Delta ln\mathrm{USD/JPY}_t + \beta_8 FFrate_t + \varepsilon_t \end{aligned} \tag{20}$$

The results are in Table 6 and show that some variables are statistically significant in Bitcoin equation (Eqn. 19), while no significant variables found for Ethereum (Eqn. 20). This uncorrelation indicates that the cryptocurrency moves independently from the major economic variables, therefore has a high hedging capability overall. The significance found in intercept and AR term presents the opportunity for arbitrage because they are observable beforehand. The negative correlation found in the log return on EUR implies that bitcoin could partially offset the loss when the dollar depreciates. However, because of the small coefficient and the significance level (p-value: 0.055), the effect is limited or even negligible.

Next, the residuals are examined to see whether the heteroskedasticity exists for the residuals in the previous models. Figure 5 and Figure 6 are the visualizations of residuals from Eqn (19) and (20), respectively, and they show that Bitcoin has it decreasing over time, whereas Ethereum shows similar but is not as clear as bitcoin is. To validate it, Lagrange multiplier test for the ARCH is implemented. The test statistics follow chi-square of one degree of freedom. The results show that bitcoin equation has residuals heteroscedastically distributed, whereas Ethereum equation rejects the null hypothesis at 10% significance level, but narrowly accepts the null hypothesis at 5% level. However, separate regression using only lagged variable showed the p-value of

0.0498 in the same test, so I conclude there is a heteroscedasticity for the residuals of the ether return too.

Variable	Bitcoin Equation	Ethereum Equation
Intercept	2.68825**	-1.19410
	(1.13610)	(8.88340)
BTC return_{t-1}	0.05827**	
	(0.02769)	
ETH return_{t-1}		-0.01887
		(0.06001)
$\Delta \text{lnSP500}_t$	0.06981	-0.55392
	(0.24927)	(0.70619)
$\Delta \text{lnSTOXX50}_t$	0.00316	0.82851
	(0.18348)	(0.52436)
$\Delta \text{lnNIKKEI225}_t$	-0.04766	-0.29320
	(0.14017)	(0.36615)
ΔlnGOLD_t	0.26044	0.16902
	(0.17059)	(0.59269)
$\Delta \text{lnUSD/EUR}_t$	-0.02292*	0.04510
	(0.01192)	(0.07582)
$\Delta \text{lnUSD/JPY}_t$	0.41541	-0.45811
	(0.31215)	(0.80681)
FFrate_t	-0.32022	0.83843
	(1.19410)	(2.39733)
Observations	1326	275

Standard errors in parentheses

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 6: The results of AR (1) with explanatory variables. The returns of bitcoin and ether as a dependent variable, respectively.

Equation	Test Statistics	P-value
BTC: equation (19)	73.41	0.0000
ETH: equation (20)	3.70	0.0543

Table 7: LM ARCH test.

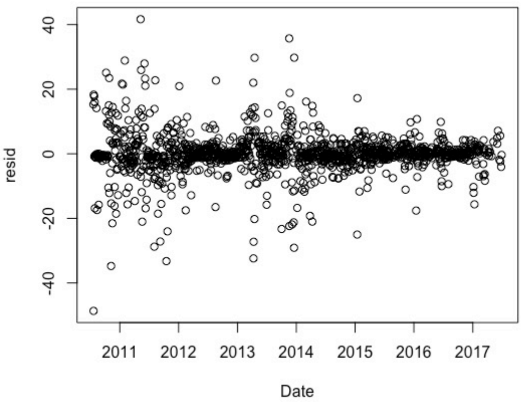

Figure 5: Residuals of Eqn (19)

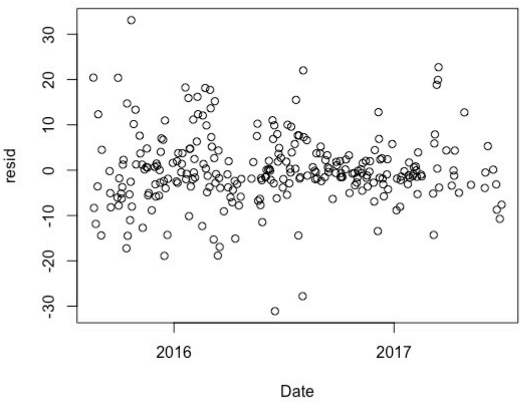

Figure 6: Residuals of Eqn (20)

Next, univariate AR (1) + GARCH (1,1) models are formed to examine the historical trend of return and volatility of bitcoin and ethereum. The formulae are described as follows:

$$BTC\ return_t = \beta_0 + \beta_1 BTC\ return_{t-1} + \varepsilon_t \tag{21}$$

$$ETH\ return_t = \beta_0 + \beta_1 ETH\ return_{t-1} + \varepsilon_t \tag{22}$$

$$\varepsilon_t = \sigma_t v_t \tag{23}$$

$$v_t \sim N(0,1) \tag{24}$$

$$E[\varepsilon_t^2 | \Omega_{t-1}] = \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{25}$$

The results are in Table 8. Both β_0 and β_1 are statistically significant in BTC return equation, indicating the average positive return and time dependency of bitcoin return. In Ethereum on the other hand neither is statistically significant. Equation (22) therefore is transformed into equation (26), in which the return is determined completely randomly. The result is in the last column of Table 8.

$$ETH\ return_t = \varepsilon_t \tag{26}$$

Variables	BTC return	ETH return (AR+ GARCH)	ETH return (GARCH)
Conditional mean	0.21460**	0.30588	
[β_0]	(0.06568)	(0.19337)	
AR(1) [β_1]	0.07475**	0.02822	
	(0.02559)	(0.04526)	
Conditional	0.88971***	2.32547***	2.54717***
variance[ω]	(0.10399)	(0.66791)	(0.72064)
ARCH(1) [α_1]	0.26699***	0.34632***	0.37871***
	(0.02551)	(0.05553)	(0.05793)
GARCH(1) [α_2]	0.75627***	0.68431***	0.65931***
	(0.01669)	(0.03505)	(0.03687)

Standard errors in parenthesess

**** p < 0.01, ** p<0.05, * p<0.1*

Table 8: The results of the GARCH (1,1) with the return of bitcoin and ether as dependent variables

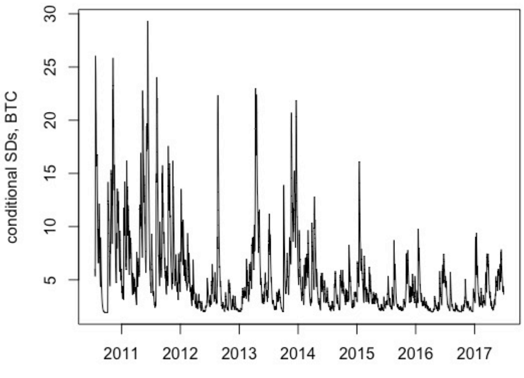

Figure 7: Historical volatility of bitcoin

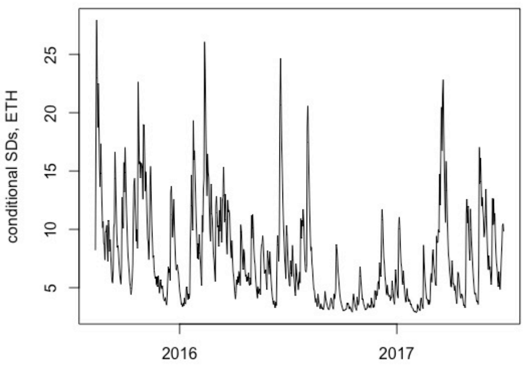

Figure 8: Historical volatility of ether

The time dependency is again confirmed in bitcoin mean equation, indicating the opportunity for arbitrage. However, the coefficient has remarkably decreased. Investors can expect an average positive return of 0.2 percent and predict 0.07 percent of the return from the previous observation. This value is small enough to be concluded as negligible.

In terms of the variance, ω, α_1 and α_2 are statistically significant, indicating the volatility of both bitcoin and ether are dependent on the one of the previous period. That can be cross-validated from the historical conditional volatility charts in Figure 7 and Figure 8 for bitcoin and ether, respectively. Both confirm the existence of volatility clustering. Figure 7 and 8 also indicate that the general trend of the volatility is shrinking over time both in bitcoin and ether. Although the volatilities are shrinking in both cryptocurrencies, this tendency is more striking in bitcoin. As discussed in Section

1 and Section 2, the large volatility of cryptocurrency is one of the biggest challenges that cryptocurrencies are facing in order to function as a bona fide currency, because this is the underlying factor that prevents cryptocurrencies to satisfy the three criteria of money. This finding is consistent with the previous studies such as Cermak (2017) of the investigation into bitcoin, but it is important to point out that ether has the similar trend but is not as clear as bitcoin is. In this sense, Bitcoin is in a better position to function as money than Ethereum is. Yet, the absolute level of volatility is still very high both in bitcoin and ether, compared to the ones of major currencies and gold. Figure 9, 10 and 11 are the historical conditional volatility of Euro, Japanese Yen, and Gold, denominated by US dollar. The volatility is a bit higher in gold but much lower than cryptocurrencies are. Therefore, a cryptocurrency functioning as a bona fide currency is still a long way off.

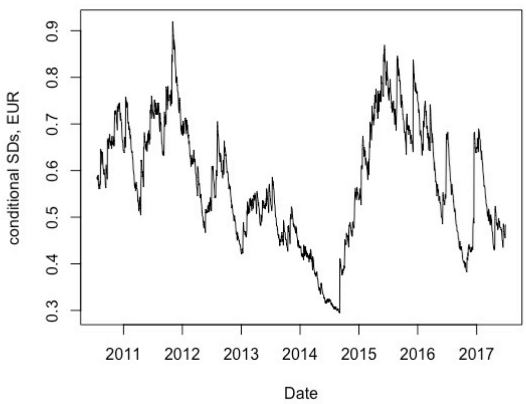

Figure 9: Historical volatility of Euro

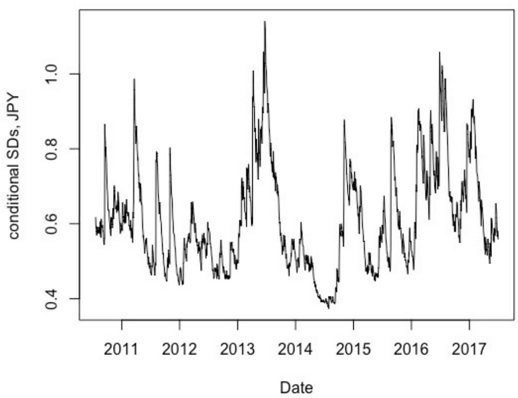

Figure 10: Historical volatility of Yen

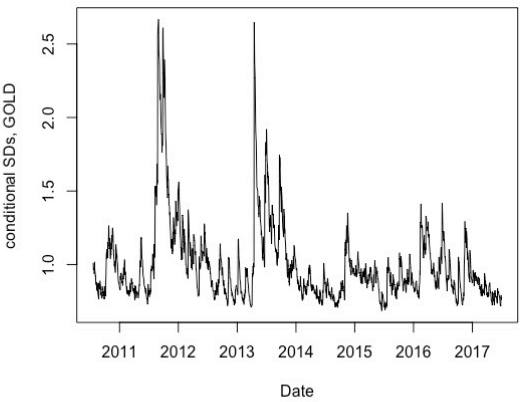

Figure 11: Historical volatility of gold

6. Discussion and Conclusion

In this paper, I investigated the hedging capabilities of cryptocurrencies and whether they can function as a bona fide currency. At first, I introduced the concepts and definitions of the terminology used in this paper and identified three features of digital currencies. These include that they are assets with no intrinsic value and price is determined by supply and demand, that they have own self-sufficient payment mechanism, and that there is no arbitrary institutional arrangement. I then focused on Bitcoin and Ethereum, two of the most used cryptocurrencies in terms of the market capitalization. These two currencies are different in the sense that Bitcoin is digital money while Ethereum an application platform for a smart contract. I implemented two separate models for Bitcoin and Ethereum. The methodology I used is the AR(1) with exogenous explanatory variables and the univariate GARCH(1,1) with AR(1) process for the mean equation. The empirical results showed that both Bitcoin and Ethereum do not have a significant explanatory variable, indicating that the movement of the price of cryptocurrencies is independent of the shocks to the major economic variables, hence the similar hedging capabilities of both digital currencies. Therefore possessing a cryptocurrency in a portfolio can mitigate the risk as a good hedge against the negative events of the major economies. As for the monetary aspect of the cryptocurrency, both bitcoin and ethereum do not satisfy any of the criteria for money largely because of its high volatility. The GARCH (1,1) model analysis showed the existence of volatility clustering, and the volatility is becoming smaller in recent years. This implies that the cryptocurrency is on its path to function as a currency, albeit not soon. On top of that, the comparison of the result of the absolute level of volatility and the pace of shrinking is faster in Bitcoin than in Ethereum, which implies Bitcoin's bigger potential to become a bona fide currency.

Yet, it is important to point out the limitations of the methodology implemented. In the process of obtaining stationarity, I implemented the first differencing of log return, which is a typical method of dealing with time series data with a unit root. This approximation is known to be accurate when the return is close zero. However, the log return diverges from the arithmetic return as the return increases. As discussed, the rate of return in cryptocurrencies is high, and in some cases it is confirmed that this divergence reached more than 10%. It is possible that this distorts the result to some extent. Additionally, I only considered the exogenous macroeconomic variables in this model and failed to include endogenous variables, for example, the changes in the amount of supply and security breaches. Also, since a cryptocurrency is a relatively new concept and is not supported by the government decree as fiat currencies are, external events such as the changes in a government regulation have a great impact on investors mind. In January when Peoples Bank of China announced its plan to limit the outflow of the capital, the price of bitcoin has dropped 20% just within 2 hours (Smith, 2017). Including these variables is likely to improve the accuracy of the model. On top of that, the standard GARCH model assumes both negative shocks and positive shocks to behave similarly, which may be a rather strong assumption in the case of cryptocurrency.

Another limitation of the analysis is the dataset. The analysis of Ethereum is based on the exchange price retrieved from a single exchange. This is because of the unavailability of the price index for Ether, as in BPI for the bitcoin price. The price does not differ a lot because Ethers that the exchanges sell or buy are identical, but this loses some accuracy. Also, I covered the almost entire period where data is available for this study, including when the price was less than ten cents. It is questionable whether the same interpretation is possible for the early period and the late period. Another point is the choice of cryptocurrencies. In this study, I examined two of the most famous cryptocurrencies, but there are more than 800 cryptocurrencies, some of which are designed to overcome the challenges of the blockchain. For example, EOS is a new smart contract platform based on a cryptocurrency token. This cryptocurrency, according to its white paper[x], is able to process millions of transactions per second, which significantly improves blockchain's scalability problem (Stanley, 2017).

For the future researches, it is recommended to elaborate the original model using,

[x] https://github.com/EOSIO/Documentation/blob/master/TechnicalWhitePaper.md (Accessed on August 14, 2017)

for example, the level of supply and the dummy variable for the regulatory changes, as well as including other small exchanges for Ethereum and extending the research into other cryptocurrencies. It may be better to replace standard GARCH with extended GARCH models, for instance, exponential GARCH (EGARCH) to allow for the asymmetric behavior of negative events and positive events, or integrated GARCH (IGARCH) to include a permanent effect of a particular shock such as a regulatory change.

References

Baur, D. G., & Lucey, B. M. (2010). “Is Gold a Hedge or a Safe Haven? An analysis of Stocks, Bonds and Gold.” *Financial Review*, *45*(2), 217-229.

Bollerslev, T. (1992), “Generalized Autoregressive Conditional Heteroscedasticity, ” *Journal of econometrics,* 31(3), 307-327

Brandvold, M., Molnár, P., Vagstad, K., Valstad, O. (2015), "Price Discovery on Bitcoin Exchanges,” *Journal of International Financial Markets, Institutions & Money*, 36, 18–35

Capie, F., Mills T.C. & Wood, G. (2005). "Gold as a Hedge Against the Dollar," *Journal of Institutional Financial Markets, Institutions and Money,* 15(4), 343-352

Cermak, V. (2017). “Can Bitcoin Become a Variable Alternative to Fiat Currencies? An Empirical Analysis of Bitcoin's Volatility Based on a GARCH model," Retrieved from SSRN: https://ssrn.com/abstract=2961405

Coindesk (2017), “State of Blockchain Q1 2017,” *Coindesk,* retrieved from: https://www.coindesk.com/state-blockchain-q1-2017-pdf/ (accessed on June 13, 2017)

CPMI (2015), “Digital Currencies,” *Bank for International Settlements*, retrieved from: http://www.bis.org/cpmi/publ/d137.pdf (Accessed on June 6, 2017)

Dickey, D. A., & Fuller, W. A. (1979). “Distribution of the Estimators for Auto-regressive Time Series with a Unit Root,” *Journal of the American Statistical Association*, *74*(366a), 427-431.

Dwyer, G. P. (2015). "The Economics of Bitcoin and Similar Private Digital Currencies," *Journal of Financial Stability*, *17*, 81-91.

Engle, R. F. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica: Journal of the Econometric Society,* 50(4), 987-1007

Glaser, F., Haferhorn, M., Weber, M.C., Zimmermann, K., Siering, M. b (2014), "Bitcoin. Asset or Currency? Revealing Users' Hidden Intentions," ECIS 2014 Tel Aviv. Available at SSRN: https://ssrn.com/abstract=2425247

Goldman Sachs Investment Research. (2014). “Global Macro Research: Top of Mind,” *Goldman Sachs*, 21, 8, March 11, retrieved from: http://www.paymentlawadvisor.com/files/2014/01/GoldmanSachs-Bit-Coin.pdf

Hamilton, J. D. (1996), *Time Series Analysis,* Princeton, Princeton University Press, 43-48

Hansen, P. R., & Lunde, A. (2005). "A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH (1, 1)?," *Journal of Applied Econometrics*, *20*(7), 873-889.

Haubno-Dyhrberg, A. (2016a). “Bitcoin, Gold and the Dollar - A GARCH volatility Analysis -,” *Finance Research Letters*, 16, 85-92

Haubno-Dyhrberg, A. (2016b). “Hedging Capabilities of Bitcoin. Is it the Virtual Gold?,” *Finance Research Letters*, 16, 139–144

Hertig, A. (2016). “How Will Ethereum Scale,” *Coindesk,* Retrieved from: https://www.coindesk.com/information/will-ethereum-scale/ (accessed on August 16, 2017)

Hill, K. (2014). “*Secret Money: Living on Bitcoin in the Real World*,” New York, Forbes Media

Mankiw, N. G. (2015). “*Macroeconomics,*" 9th Edition, New York: Worth Publishes, 82-85

Nakamoto, S. (2008). "Bitcoin: A Peer-to-Peer Electronic Cash System," retrieved from: https://bitcoin.org/bitcoin.pdf (accessed on August 2, 2017)

Okimoto, T. (2010). “*Metric Time Series Analysis,*” Tokyo, Asakura-Syoten, 147-161 [Written in Japanese]

Smith, G. (2017). “How a China Crackdown Caused Bitcoin’s Price to Plunge,” *Fortune,* January 5, retrieved from: http://fortune.com/2017/01/05/bitcoin-plunge-china-currency/ (Accessed on August 14, 2017)

Stanley, A. (2017). “EOS: Unpacking the Big Promises Behind a Possible Blockchain Contender,” *Coindesk,* June 25, retrieved from: https://www.coindesk.com/eos-unpacking-the-big-promises-behind-a-possible-blockchain-contender/ (Accessed on August 14, 2017)

Szetela, B., Mentel, G., & Gędek, S. (2016), “Dependency Analysis between Bitcoin and Selected Global Currencies," *Dynamic Econometric Models*, *16*(1), 133-144.

Tully, E., Lucet, B. (2007). "A Power GARCH Examination of the Gold Market," R*esearch in International Business and Finance*, 21 (2), 316-325

Vorick, V. (2016). "Ensuring Bitcoin Fungibility in 2017 (and beyond)," *Coindesk,* December 28, retrieved from: https://www.coindesk.com/ensuring-bitcoin-fungibility-in-2017-and-beyond/ (accessed on August 8, 2017)

Vukolić, M. (2015). "The Quest for Scalable Blockchain Fabric: Proof-of-work vs. BFT Replication," In *International Workshop on Open Problems in Network Security* (pp. 112-125). Springer, Cham. Retrieved from: https://allquantor.at/blockchainbib/pdf/vukolic2015quest.pdf (accessed on August 16, 2017)

Yermack, D. (2013). "Is Bitcoin a Real Currency? An Economic Appraisal," *National Bureau of Economic Research*. Retrieved from: http://www.nber.org/papers/w19747.pdf (accessed on August 11, 2017)