VALUE ANALYSIS OF BITCOIN

An Empirical Analysis on Return and Volatility

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Abstract

This study analyzes the changes in Bitcoin returns and volatility using daily data in the period of 19th July 2010 to 28th August 2018 denominated in US dollar. Bitcoin price fluctuates dramatically by the macroeconomic, speculative and the fundamental factors. Beyond the macroeconomic and internal determinants, some specific events which create uncertainty in the political and financial areas are studied. OLS regression is applied to examine the returns. Chinese Yuan is a significant determinant of predicting the Bitcoin returns. One of the most distinctive characteristics of Bitcoin is its volatility. A symmetric GARCH model is practiced investigating the volatility. There is evidence that the volatility of Bitcoin follows the variation of Chinese Yuan rate against the US dollar at the next period. The volatility in Yuan has predictive power in Bitcoin's volatility. The last significant finding is that Bitcoin acts as an alternative investment asset in the US during uncertainty in the stock market.

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Introduction

Bitcoin is a groundbreaking digital technology with the potential to radically change the way of banking and investing. Even though it has a very volatile nature compare to the fiat currency, it revalorizes the utilizing strategies of money and portfolio. The primary novelty of Bitcoin is free commerce globally. The economy of the entire world is conducted by fiat currencies, and the decisions governments take. These decisions affect the wealth of the citizens through the interest rate, inflation and several more macroeconomic factors reduce the wealth. Bitcoin eliminates this amount of disposal wealth by the favor of its unique properties. It becomes a significant competitor against the fiat currencies. The potential legitimacy of Bitcoin creates a big challenge to deal for the governments in many respects due to Bitcoin's unique features.

One of the essential characteristics of Bitcoin is decentralization. This means that there is no central authority behind it to control it as opposed to fiat currency. Hence, no government, bank, and institution can intervene transactions of Bitcoin and impose transaction fee. Consequently, users have the absolute control over this currency. Even if the governments illegalize it, it cannot be stopped to use. For example, Chinese regulatory authorities had imposed a ban on crypto-trading in September 2017, but the attraction of Bitcoin continues to grow. The results of this study also provide a shred of evidence for this feature.

The second advancement is the instant transactions that Bitcoin enables while transferring money from one bank account to another takes few days. Bitcoin's transaction occurs instantly and final differing from credit cards, also. The credit card transactions finalize fully in months.

Another disruptive property is transaction fee which is almost zero. While banks charge up to 10% on transferred amount, Bitcoin's transporting cost is practically free like 0.01 cents. This transactional cost does not depend on the amount and geographical location. According to 2018 World Bank report, $642 billion is predicted to transfer as global remittances. While the average cost of international transfer is $200 that is 7.1% of the first quarter of 2018, Bitcoin has almost no cost. This means that people can potentially save a significant amount of money.

Everyone can use Bitcoin regardless of credit score, size of income or collaterals like banks usually ask. It has the potential to facilitate commerce more than fiat currency does. It is an open source to everyone who has internet access.

The last distinctive feature to mention is its security system. Bitcoin itself is not hackable. However, exchange platforms and Bitcoin store services can be hacked. Every user has a unique key that uses cryptography.

While these unique features can be considered as pros compared to the fiat currency, there are some cons concerning legality, legitimacy, and volatility. Legal questions have arisen due to using easiness of Bitcoin in illegal activities. The black market "Silk Road" is the most notable case what extent the digital currency loosens up the criminal activities. Even if all governments recognize it as legal, it still has to pass a challenging test that is trust and acceptance by the whole world. Because the most critical part of sustainability is the network that requires a great adaptation based on faith. The last and one of the main concerns of this study is the volatility of Bitcoin which prevents the precautious users and investors to use it with confidence. According to Credit Suisse's report (2017), Bitcoin has 11 times more fluctuated than the exchange rate of GBP denominated in USD even after the Brexit period. Its price changes are unpredictable. By using GARCH(1,1) model in the following sections, the volatility is studied if any factor can predict it.

Regarding the price fluctuations, Bitcoin price changes are the main focus of this study, first ever use of cryptocurrency, online trade was on May 22nd, 2010 by a computer programmer for two pizzas with the amount at 10,000 Bitcoins (Yermack, 2013) which was equivalent to $155.80 million in December 2017 (Sovbetov, 2018). For the first time, Bitcoin was traded at $0.07 per unit in 2009. When Bitcoin price skyrocketed over $1000 in 2014, then mainstream interest kindled in cryptocurrency, especially in Bitcoin. In December 2017, Bitcoin Price Index recorded an all-time high value of $ 19,783.21 (source: CoinDesk), raising warnings from one-side of financial analysts that it is a bubble. It can be seen that the currency is extraordinarily volatile. The average annualized volatility is over 5000% (De Vries and Aalborg, 2017), indicates that volatility is the main problem of Bitcoin. At the beginning of 2018, its market capitalization is near 195 billion USD, exceeds the GDP of over 130 countries, representing about 43% of the total estimated cryptocurrency capitalization which has the largest cap among all cryptocurrencies.

Financial markets react sensitively to political upheavals, crises or shocks in both ways. Unexpected or uncertain situations reflect assets prices immediately. Therefore, returns and volatility change over time. This indicates that the process is conditionally heteroskedastic. In this context, studying Bitcoin price changes is significant since it has already started to take part in portfolios as an asset. Besides, a considerable number of merchants has begun to accept Bitcoin as a medium of exchange. To understand its dynamics of price changes is crucial for portfolio managing and possibly usage as an alternative fiat currency in the future. The excessive volatility of it may cause huge losses. It has the potential to penetrate into the financial structure deeply. However, the determinants affect its price are uncertain yet. This study investigates these factors by considering the ones also influence the financial markets and if there are any similar patterns.

2016 has become a year of revitalization for the Bitcoin, and drastic price changes occurred throughout 2017 in the following. In the meanwhile, financial markets around the world were surging. The fluctuations in Bitcoin price during these years can be seen in Figure 1 may be attributable to the macroeconomic factors including uncertainty in markets mainly in China and the US. These countries have arguably played a significant role consistent with the traded volume compared to other countries. Due to its speculative nature, the price volatility is mostly affected by external events. This research examines the Bitcoin price formation and the volatility regarding external determinants. To prevent or reduce the possible financial damages to unwary investors, it is critical to understand what affect the Bitcoin movements.

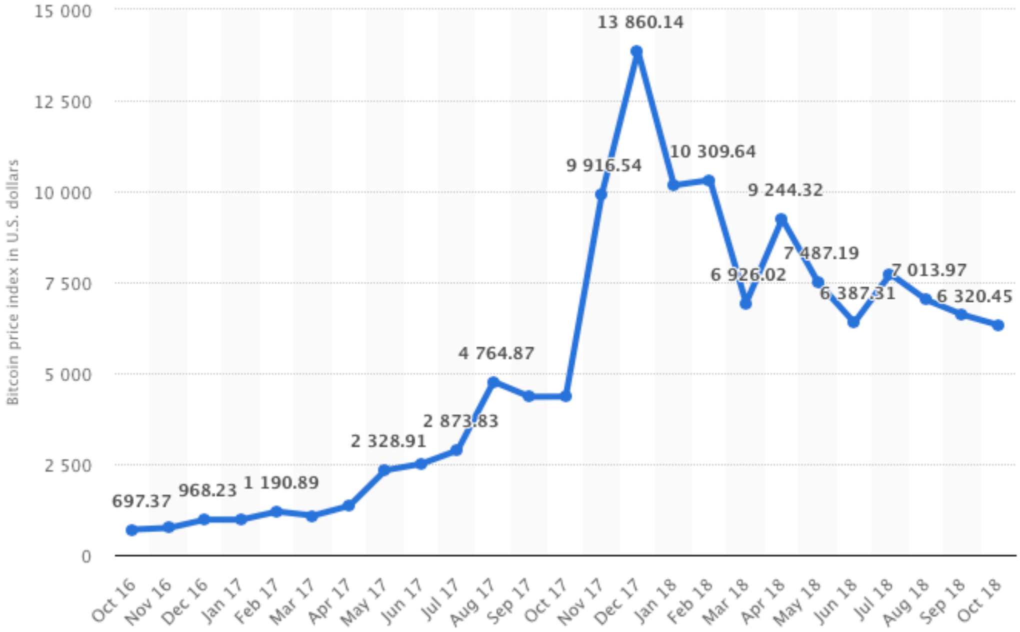


Chart 1: Bitcoin price in USD between 2016-2018 (source: statista)

Even if Bitcoin is used as a currency in more than 100,000 online stores (Brandom and Franzen, 2014), the ongoing debate addresses whether Bitcoin is used as an investment asset more than as a payment system. Glaser et al. (2014) find evidence to support the case of Bitcoin as an investment asset. This research also treats Bitcoin as a speculative investment asset rather than a fiat currency due to its excessive volatility and a limited number of acceptances as payment. Considering all variables, this study examines Bitcoin as an investment tool but not as a medium of exchange.

In the academic literature, Bitcoin's technical and legal aspects are studied more than its financial and economic perspective until a few years ago. This makes cryptocurrency market search still relatively scarce concerning price formation or other financial aspects which is the point of origin of this research.

Most popular virtual currency is sampled which is Bitcoin to investigate how this currency interact with the stock markets (SP500, SSE, DAX, CAC40, and FTSE100).

OLS method is used as a preliminary insight in returns. Following that symmetric GARCH model is used to analyze the volatility of Bitcoin. Last, event dummies are added to the GARCH model to capture the political and announcement events effects on the Bitcoin volatility. The main findings are that Bitcoin reacts to only Chinese Yuan exchange rate against US dollar. Another result is when uncertainty arises in the political and financial environment, investors' tendency is to seek alternative assets other than stocks. Bitcoin price significantly increased after Trump won the presidential election of US immediately.

This paper proceeds as follow: Section 2 discusses the current relevant state of literature. Section 3 describes the data, the data transformation, and the main research question. Section 4 provides the methodologies adopted, while Section 5 presents the results and concluding remarks.

Literature Review

Bitcoin has experienced many boom-and-bust episodes, cyber-attacks, regulation attempts by authorities and bans from governments. Even though there had been attempts to invent digital currency during tech boom 90s, they did not survive until Bitcoin due to financial, organizational and technical problems. Above all, these digital currencies were required to verify by trusted third parties that are the companies invent them. Most of the time along with these failed companies when dotcom bubble exploits; these currencies were dragged down as well. Its popularity made a breakthrough following failures of governments, central banks, and traditional banks. The most significant two events that caused Bitcoin appeared are 2008 Financial Crisis and European Debt Crisis in consequence of losing faith to central banks and fiat currencies. Nowadays, crypto is beyond anarchists and people who have lost their trust to their governments, traditional banking system, and financial institutions; they take place in investors' portfolio as a speculative investment tool and hedge against the fiat currency and financial markets against uncertainty. Because it can be traded on exchange platforms, it is comparable to the financial products which investors expect gains with the appreciation in the future. In the third quarter of 2018, almost 22 million wallets are recorded in bitinfocharts.com. However, it is likely to less than that number because some users have more than one account due to privacy and lost account issues. From 2.9 to 5.8 million of them are actively using while the most are buy-and-hold investors according to a Cambridge University research (Global Cryptocurrency Benchmarking Study, 2017). Sovbetov (2018) describes the cryptocurrency 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 of the currency''. As can be observed that the size of the active users is less compared to buy-and-hold investors. This shows that investors mainly hold to realize potential returns in the future rather than using for daily consumption activities. Yermack (2013) argues that it can serve only as a speculative investment tool due to its high volatility. Considering the regular payment methods such as Visa, MasterCard or PayPal, Bitcoin possesses the tiny portion as a payment method. While at most 5.8 million users use for spending, Visa has 755 million credit cards in circulation globally in the first quarter of 2018 (source: statista). However, the currency functions increasing as real currency in some environments; accepted as a payment method by many merchants. Over 100,000 merchants worldwide accept bitcoin currently for shopping, for instance, Subway, Microsoft or Apple. Even though they are majorly online retailers, there are also physically existed shops where accept such as Reeds Jewelers, cafes or restaurants.

Bitcoin is a unique asset and spreads far and widely into the financial system; it requires to be investigated profoundly but taking into consideration as different than traditional currencies and financial products. This implies that macroeconomic indicators do not affect the prices of Bitcoin in the same way as a national currency and traditional assets. Fundamental metrics to evaluate the value of stocks do not work on Bitcoin. Fundamentals of it prevent to determine a fair price because the price depends on the investors' expectations about the future value and speculations. The basics of the fiat currency which is supply-demand do not perform on Bitcoin's value because there is no central institution to monetize it indicates that decentralization (Kristoufek, 2013).

One of the most distinguished features of the virtual currency is not being issued and regulated by a central bank and a government that makes it stay entirely outside the administrative borders of any country and its politics. It is eliminated from all financial controllers. On the other hand, this unique asset generates a new tendency in the financial markets and investment portfolios. Bouoiyour and Selmi (2017) show the role of Bitcoin as a hedge which means negative relationship can be observable with stock prices, indicates that Bitcoin offers a safe haven during uncertainty environment in the markets. They argue that this feature of it provides a profit when political and economic uncertainty rise and faith in banking and governmental system decrease. By decentralizing the currency, it offers an alternative investment in times of increased risk in the stock markets. Bouriazzi and Dyhrberg (2016) support this statement by demonstrating that Bitcoin and stock markets move oppositely in particular before 2013 indicates that hedging capability of the digital currency against US dollar. They detect that investors inflow Bitcoin attributable to the safe-haven property, especially the before 2013 Bitcoin price crash. However, they also mention that Bitcoin has lost its safe-haven feature against US dollar after the crash.

The major consensus in the academic literature is that the Bitcoin as an investment tool and a speculative asset rather than an alternative to fiat currency due to its volatility. Yermack (2015) showed that Bitcoin is more suited to be a speculative investment tool instead of a fiat currency due to its extreme volatility. Gronwald (2014) states that the Bitcoin market is highly inefficient and extremely volatile. However, Bouoiyour and Selmi (2016) find out a decreasing trend in its volatility over time. When Urquhart (2016) considers the Bitcoin efficiency from Fama (1970) viewpoint, he observed that Bitcoin has become more efficient by the time as more investors trade though it is still significantly inefficient. They all except Gronwald accept that the price is more stable than before. In the meanwhile, El Bahrawy and Alessandretti (2017) examine the behavior of the entire market (1469 cryptocurrencies). They find that the cryptocurrency market also has been more stable for years concerning some specific aspects such as market share distribution and the turnover of cryptocurrencies become quite stabilized, while their market cap increases exponentially. On the other hand, its inefficiency may not be specific to Bitcoin since the other all immature markets show similar features. But it is important to highlight that Bitcoin is still far from entering the market as fiat currency since it does not meet the requirements of being. There are three traditional currency roles accepted universally; medium of exchange, unit of measurement, store of value. On the other hand, Bitcoin is increasingly accepted in the real economy as a means of payment. Bitcoin-accepting rate increases at a larger rate than previous quarters in 2017. In the first and second quarter of 2017, the adoption rate by businesses is 5.5% and 5% respectively. A slight and steady growth can be observed. In the third and fourth quarter, the rates are 8.5% and 12% respectively where the great interest begins. The price rises 7%, 135%, 74% and 224% respectively during 2017 (source: cointelegraph). These price and adoption rate surges are driven by some factors such as the launch of Bitcoin future markets by CBOE or Bitcoin ETFs recording by NYSE. Even though investor interest rising rapidly, the total market capitalization of all virtual currencies is 610,112,000,000 USD as of December 31, 2017, which is still embryonic relative to NYSE above 21 trillion USD. According to Goldman Sachs' report (2018), cryptocurrency represents 0.3 percent of world GDP as of mid-2018. The current market capitalization of Bitcoin is above $111 billion (2018). Since cryptocurrencies have started to take part in portfolios as an investment, investigating of their price changes and volatilities especially the largest ones are highly significant to be able to make the profit, diversify and manage a portfolio (Dyhrberg, 2016a).

Bitcoin is introduced as a medium of exchange since it is peer-to-peer electronic decentralized payment system according to Satoshi's nine pages manifest, but it is used mainly as an investment asset to make the profit with increased value in the future since its volatility is exceptionally high and not accepted by most merchants. Katsiampa (2017) argues that the Bitcoin market is highly speculative by using AR-CGARCH model as a result of comparing GARCH models. Glaser et al. (2014) investigate the movements of Bitcoin by using GARCH model and find out that investors use it mainly as an alternative investment asset rather than a transaction method in particular. This buy-and-hold trend forms due to the critical feature of Bitcoin. It is a limited resource that is the maximum amount of 21 million. 80% of it is in circulation means that are already mined. As its nature, Bitcoin is deflationary because it is a predetermined amount of resource means that its purchasing power increases over time. From the traditional perspective, it is also inflationary; the rate diminishes until all Bitcoins are mined since the supply of Bitcoin increases over time. Besides, Bitcoin shows similarity with gold. They both show a common characteristic which is scarcity. In case of increasing demand in the future when all bitcoins are mined, this means that it becomes deflationary and its value increases. Therefore, rational investors hold it as an investment asset in their portfolios with the hope that its value will grow in the future like gold. This points out that they are both mainly used as a store of value. Cermak (2017) argues that even though it cannot supersede to fiat currency definitely due to structural and economic issues but can behave as an alternative to it. One debate is the mining Bitcoin process consumes a considerable electrical power. When it is compared with the cost of ATMs around the world, it still requires less energy according to the report published from Institute Mines-Telecom (Walebroeck, 2018). However, the mining cost can rise enormously as the amount of Bitcoin to mine decreases and the mining gets more challenging. This difficulty also may diminish the incentive or cause to gather the mining power in few hands. On the other hand, the revenue obtaining from each Bitcoin increases. It is not known yet which one dominates to other; the cost or the revenue. This issue confronts with another in case the mining is not profitable due to high costs. Then, the network faces a safety issue which is called majority attack. Unless the power used to mining is more than the hacking the system, it remains secure. Besides these, it has faced a prejudicial issue. Although there is a bad reputation about bitcoin due to attracting illegal activities, it makes possible small transactions internationally, almost no cost no matter which location it is sent, and for people have no bank account or work online from a distance and anonymously. The notorious black-market Silk Road where bountiful illegal selling takes place was the critical catalyst of Bitcoin usage and community expansion (Vigna and Casey, 2016). It started to have media coverage very often and catch public attention. Another catalyst Mt. Gox is the first and, the biggest Bitcoin exchange platform based in Japan also helped to make Bitcoin legitimize an investment tool and boosted the number of users more and more. Silk Road busted in 2013 and Mt. Gox went bankrupt in 2014. But their effect on raising Bitcoin network and reaching the broad masses are significant via media mainly. Because of these features; decentralization, anonymity, and irrevocability, bitcoin and all other cryptocurrencies come under fire by governments and regulatory agencies, but they do not have the authorization to impose control on it. For example, China banned cryptocurrency trading in 2017. People still kept trading. Other countries such as the US, Japan, and South Korea attempt to improve the security of trading platforms instead of banning as crypto market increases in size rapidly.

The keystone of Bitcoin is its technology Blockchain. It is the turning point that attracts investors, academics and entrepreneurs." Blockchain, a software that provides a public distributed ledger where any party has the authorization to effect included the founder of Bitcoin to record every transaction. As opposed to public ledger book-keeping, central banks and regulatory authorities hold centralized ledger. As this centralization provides the security to the public, it holds excessive power and profit for a small group of head people. Because Blockchain relies on cryptography for safety and it is a software, there is no need to know one another. Every transaction is broadcasted in the network through transparent updates of information every ten minutes to confirm based on absolute consensus by miners who are public. Once a transaction is verified, it is irreversible. Miners' incentive is the reward for solving the algorithm of a transaction and add a new block at the end of the previous block. The software allocates the book-keeping task to the public to obtain security and trust in return to decentralization instead of centralization (Vigna and Casey, 2016). Since blockchain proved its secure and fully transparent system, there are more fields other than Bitcoin to be used such as an online electoral process, self-enforcing contracts, and asset sharing agreements. Furthermore, China has built a Blockchain system that digitizes checks that could replace paper checks issued by domestic businesses. This system makes possible a clear overview of a digital check throughout the whole cycle to regulators, and it reduces the cost of manual cross-checking for transactions. Hence, blockchain technology is the most significant innovation that materialized Bitcoin. Following this, Bitcoin is the inspiration to other cryptocurrencies launched currently more than 1000. The system is the fountainhead of Ethereum. It is the second most valued and disruptive cryptocurrency and has recorded as the fastest rise a digital currency. Ripple is the third most valued cryptocurrency.

Since cryptocurrency is completely computerized mathematically and based on cryptography, it is considered as unhackable. However, there are still security vulnerabilities which are theft and seizure of Bitcoin in particular in case of Mt.Gox 473 million dollar disappearance corresponding to 7% of all Bitcoin available (source: cointelegraph). Bitcoin may not be hackable, but the exchange platforms and businesses which use Bitcoin are open to attack depending on their security levels. Therefore, cryptocurrencies biggest issue is

security and thievery. As of 2018, above 800 million USD stealing occurred in crypto markets (Autonomous Research), the largest amount in Japan on Coincheck trading platform.
Another factor that makes Bitcoin unique than predecessors is decentralization neither by a government nor its founder Nakamoto. Due to centralization attached to the traditional banking and a large number of failing companies during tech-boom, the past digital currencies could not survive. The Electronic Monetary System which was Citibank's e-cash can be considered as the pioneer to Bitcoin in the sense of disruptive and peer-to-peer money system during the 1990s. But Citibank's presence was still the center of this system on the contrary of Bitcoin. The project stayed at test phase due to essentially legal and bureaucratic issues. Glass-Steagall Act was preventing banks from using speculative assets. The total shut down of e-cash occurred with the Citibank's bailout and the merger in 1999 (Vigna and Casey, 2016). As many other academic studies suppose (Cermak, 2017; Bouri, Azzi and Dyhberg, 2016; Balcilar, Bouri, Gupta and Roubaud, 2017; Bouri, Gupta, Tiwari and Roubaud, 2017; Fry and Cheah, 2016; Brandvold, Molnar, Vagstad and Valstad; 2015) European Debt Crisis (2010) and the Financial Crisis (2008) established a ground the idea of the first decentralized digital money. Because the public lost their trust to governments and central banks, who are charged the manage monetary system. Thus, people started to alternative ways to store their money and invest. The existence of many uncertainties about the future of fiat money, financial markets and emerged political issues caused investors to seek other ways to secure their money out of control of any government. Li & Wang (2017) compare early and later market which are traditional and technological adopted markets respectively. While the early market is driven by technological factors speculatively, the mature market is driven by economic factors and not affected by speculative elements. There is strong evidence that financial markets and cryptocurrency prices move in negative relationship significantly in the literature. For instance, Bouri et al. (2016) and Bouri et al. (2017) found evidence that Bitcoin has a safe-haven property against traditional assets. Also, there is evidence that specifically Bitcoin trend surged after demonetization announcement by India and Venezuela government (Bouri and Selmi 2017). Speculative and volatile nature of Bitcoin show that liquidity changes are an important indicator of cryptocurrency prices. Although the relationship between financial markets and crypto markets is synthetic, both of them are highly linked to volatility and liquidity.

The biggest obstacle of Bitcoin being means of payment is its volatility. The volatility can be observed up to 8000% between 2009 and 2014 which is remarkably higher than traditional currencies (Ciaian, Rajcaniova & Kancs, 2016), (Baek, 2015); extremely volatile relatively. Its price movement range is between $0 of its invention in 2009 and $20,000 in 2017. However, the volatility is decreasing by the time and accepting as a means of payment gradually increasing. The level of volatility currently lower than in the past as Bouri and Selmi (2016) demonstrated. Since movements of Bitcoin is extremely volatile, modeling its heteroskedasticity and discovering the reasons for its variance are one of the most challenging parts of this study and cryptocurrency literature, in general. According to Poyser' s research (2017), there are two main groups of factors that influence cryptocurrency prices as internal and external. As an internal determinant aspect, there is only a limited number of Bitcoin in circulation maximum of 21 million. New Bitcoins are released at a predictable and decreasing rate. There has been left 19.53% of the total Bitcoin that will be mined in the future, currently (source: Bitcoinblockhalf). Supply-demand is the only internal factor that affects the price directly. Ciaian, rajcaniova & kancs (2016) include both traditional and digital currency specifics into their study on Bitcoin price to provide in-depth understanding. They find out that supply-demand which is a market-driven factor has significant power on the price changes. As digital currency specific factors, investor speculation and attractiveness via online information such as Google searches are determinants on price in the short-run, but not in the long-run. The external drivers are divided into three categories that are attractiveness, legalization, some macroeconomic factors such as stock markets and political factors. This study's main focus is the macroeconomic drivers consistent with the direction of Poyser's statement.

There is no consensus about bitcoin what class is included currency, commodity or property among countries. It is considered as a hybrid between precious metals have intrinsic value and limited and fiat currency which has no intrinsic value but backed by a government and central bank and not scarce. Governments and regulatory authorities are embezzled about bitcoin and try to find a way to regulate a decentralized currency. For example, Japan first banned the usage but later it declared that bitcoin as a legal payment method in April 2017 and made explosion bitcoin acceptance, and Japanese merchants started to accept bitcoin as payment. Japan's embracing of bitcoin is seen as positive widening step worldwide. However, US Commodity Futures Trading Commission (CFTC) defines bitcoin and all other cryptocurrencies as a commodity, and financial product confirm that they are covered by the Commodity Exchange Act (CEA). They use the term for cryptocurrencies "convertible virtual currency."

Researches in major journals on cryptocurrency are still scarce especially cryptocurrencies other than Bitcoin. However, the number of studies is increasing especially for Ethereum recently. Even though Bitcoin appears in the news very often and is a phenomenon there are limited researches on the dynamics of Bitcoin price and reasons of volatility are not discovered yet. Searching price changes are crucial because these changes are the only source of profit in the Bitcoin case. There is no other way of making a profit such as interest rate gains. From this aspect, Feng, Wang, and Zhang (2017) search that if it is possible to make a profit with informed trading in Bitcoin market where price swings are incredibly volatile. They find out informed traders make positions highly before large events and make massive profits.

This paper differs from previous studies to investigate some 2016 and 2017 notable events around the world more comprehensively and their effects on the return and the volatility of Bitcoin due to emerging uncertainty in the financial markets. Analyzing these events have an impact on stock markets shockingly are essential since the appreciation of Bitcoin mainly depends on the external factors. Bouoiyour and Selmi (2016) observed that the prices react more to negative news than the positive one. Finding out whether there is a relationship with stock markets and political situation is critical to prevent investors from financial damages. In addition to that, various European markets are included in the model separately for the first time. In previous papers, Europe is searched under European Union as a whole, and German bonds and rates are used as a benchmark which is common practice in many Europe study cases. As far as known this is the first study which is investigated how Chinese government announcements affect Bitcoin attractiveness by investors and influence their price. This study evaluates new potential and up-to-date determinants to improve current literature on Bitcoin and crypto market overall. In previous researches, the effect of Trump's victory, Brexit and the effect of the Chinese market on Bitcoin price had studied. Pichl and Kaizoji (2017) investigate the volatility of the daily return and the arbitrage opportunities between USD, EUR, and CNY. They find out that USD-CNY has the widest arbitrage spread among all. However, no research has been found for illegalization announcement by the Chinese government in September 2017 and national elections in Germany and France. Overall, this study contributes to the more-in-depth understanding of the role of the Bitcoin on the previous studies. Informative results have been found on Chinese impact on Bitcoin price building on Cermak (2017)'s research on the volatility analysis in particular.

To answer one of the questions whether Bitcoin can act as an alternative against monetary and stock depreciation at the time of rising political tension rises. Another question to answer is how Bitcoin react against announcements declared by official authorities mainly in China since it has the most trading volume and has significant power on Bitcoin.

Main Research Question

Bitcoin and the cryptocurrency market as a whole are a relatively newborn market. The fundamentals of the price of Bitcoin are not yet known in depth because the price formation of it is affected by different and unknown factors however than fiat currencies due to its unique nature. Starting from this point, the primary objective is to investigate the determinants of the price of Bitcoin.

The price of Bitcoin goes up and down significantly from day to day. Because of this volatility, also a synonym of risk, and being a new unique asset class, it has limited use in the mainstream economy. However, cryptocurrencies, especially Bitcoin's popularity is growing in high-speed among individual investors, companies, and countries worldwide. Individual and corporate investors use Bitcoin mostly as an investment tool in the long-term, but not as a daily payment for goods and services. For this reason, understanding of what leads to huge movements of prices has great importance to direct the unwary investors in order to prevent huge losses. This subject is critical to analyze deeper because it penetrates the financial markets rapidly as well as it still lacks in the literature. Moreover, it is worth to examine because of its unprecedented data inflow compared to standard currencies, a unique financial asset and rich network structure (Kristoufek, 2014).

There has been little quantitative analysis of driving factors of Bitcoin price in the academic literature. Generally, in previous studies, Bitcoin returns, and volatility were attempted to predict by using explanatory variables which were ‘Google Trends’ (Kristoufek, 2013) , ‘Transaction Volume’ (Chiu and Koeppl, 2017), ‘Trading Volume’ (Balcilar et al. 2017; Sovbetov, 2018), ‘Unique Addresses’ (Vries and Aalborg, 2017), and ‘Price Volatility Index (VIX)’ (Bouri et al. 2017; Bouri et al. 2016; Bouoiyour, 2017). In this study, another explanatory variable will be added to the regression and tested which is Bitcoin’s response to uncertainty in the financial markets due to political or governmental events. Investigation of the Bitcoin response to the global issues is relatively less in the literature. During 2016 and 2017, some outstanding political events such as Trump’s unexpected victory and Brexit vote will be included alongside previous variables. From another perspective, an addition of the last variable will answer that whether political uncertainty makes investors consider Bitcoin as a safe haven or not, thus this will lead to a surge in Bitcoin price.

Briefly, this research studies mainly how the return and volatility of Bitcoin depend on various explanatory variables that are trading and transaction volume, unique addresses and political events which increase uncertainty. Importance of the including different determinants of bitcoin price is to avoid bias in the results due to analyzing one factor at a time. As a secondary research question, does turbulence in financial markets due to political and announcement events cause changes in Bitcoin prices and to what extent of these changes? The eventual aim of this study is to provide useful information to investors while they are putting their money in Bitcoin.

Data

In the subsequent section, an empirical analysis is performed on the price changes of Bitcoin. Technical, macro-financial and political indicators that possible internal and external explanatory factors affect two particular cryptocurrencies’ performance are covered through this analysis. The selection of variables and financial data is related to movements in financial markets due to political uncertainty and governmental decisions. Datasets of both dependent and independent variables that are used to conduct this research are explained in the following part. To perform a comprehensive analysis to detect which factors affect cause price movements in Bitcoin, various factors both internal and external are included in the model. All data is collected as a daily basis for dependent and independent variables from both public and non-public resources. The dependent variable is daily Bitcoin price. The independent variables are unique addresses, trading volume, transaction volume, EUR/USD, GPB/USD, CNY/USD, S&P 500, SSE, FTSE 100, CAC 40, DAX, CRX100 and Gold Price per Ounce.

Data Description

This part provides a brief overview of data used for the practical part. The daily closing Bitcoin price that is response variable denominated in US dollars is collected from Coindesk. The Coindesk Bitcoin Price Index (BPI) aggregates prices across leading global exchanges into a price-series, therefore captures world prices more accurate than the other sources. In consideration of the disparities among exchanges, BPI is more effective than its alternatives and appropriate proxy for analyzing Bitcoin against financial and governmental uncertainty in markets and countries. All available data from 19th July 2010 to 28th August 2018, which corresponds to 2994 observations in total. One advantage of large data is that covers the early history of Bitcoin and growth phase in a significant fraction. Another advantage is the enormous value dropping of Bitcoin following the biggest crash in 2013 and bankruptcy of Mt.Gox in 2014 had been surpassed with the extended period. The Bitcoin price index covers the given period can be seen in Figure 1.

Figure 1: Bitcoin Price Index, BPI (source: coindesk)

One significant difference of Bitcoin from stock is trading days that is essential to mention. While Bitcoin is traded 7/24, stock markets are open only on weekdays. This time disparity creates an inconsistency in data between Bitcoin and stock markets. The issue is the same for gold and exchange rates variables. This means that while Bitcoin is traded 365 days in a year, all the macroeconomic and financial independent variables are traded around 250 days. This gap between the trading days causes an inconsistency between the data of the dependent and the independent variables in case of the daily data analysis. On the contrary, weekly data would not create this kind of issue. The closing price data can be considered as the opening price on Monday. However, to benefit from daily data's advantage's, this research studies with it. One of the most critical reasons that the daily regression has more predictive power than weekly regression in particular in financial time series. Changes are not observable in weekly data as much as in daily data because all the dynamics are in daily. Therefore, the detection of changes can be attributable to early warning signs. Another significant reason is that weekly data cannot deal with weekends/holidays and their lag relationship. Also, daily data provides better forecasting because days of the week have different patterns which can be identified at a daily level. To address this daily data issue, the assumption is that investors treat the Bitcoin market like regular financial markets. This implies that anything changes in the market during weekends. They take into account that the real market price is Friday's closing price valid until Monday's opening price. There is a consensus in academic literature to address in this way this weekend/holiday issue. This study's approach is in the same direction as this general assumption even though diminishing accuracy. Therefore, to avoid possible problems due to different trading patterns, weekend/holiday data is excluded from all datasets of Bitcoin.

There is a general agreement in the academic literature on which macroeconomic variables that describe the state of the economy. The variables can explain exchange rate changes, EUR/USD, GBP/USD and CNY/USD, are used as explanatory exogenous variables. As the exchange rate volatility of Bitcoin, countries which Bitcoin is traded mostly are taken into account because this currency's decentralized nature. The reason of considering multiple countries' exchange rates is because cryptocurrencies' rates are not linked with only one country's macroeconomic indicators but numerous of them jointly (Cermak, 2017). Hence, a proxy is derived which represents the countries mostly traded. The proxy data is obtained from Bitcoinity as shown in Figure 2. As can be seen that, China dominates all the other countries as the most traded currency. To find out the other two currencies following CNY, Figure 3 is depicted which CNY excluded. It shows that the USD and EUR as the second and the third most traded currencies respectively. GPB stays behind of the three most-traded currencies. In order to capture the effect of Brexit, it is included in the model.

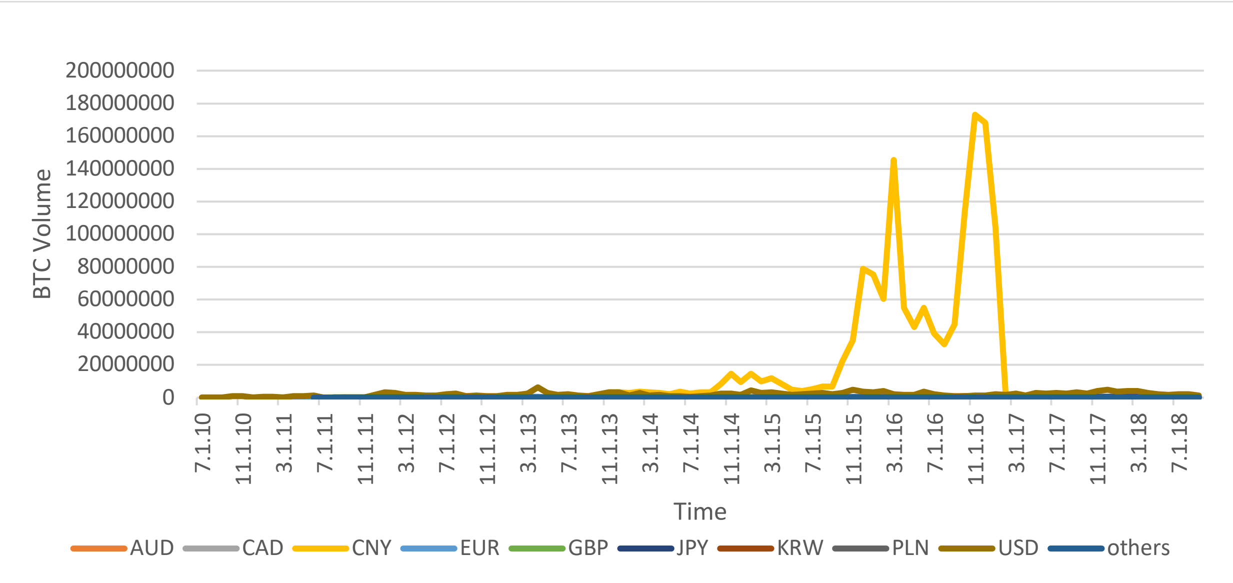


Figure 2: Bitcoin trading volume in the most traded currencies

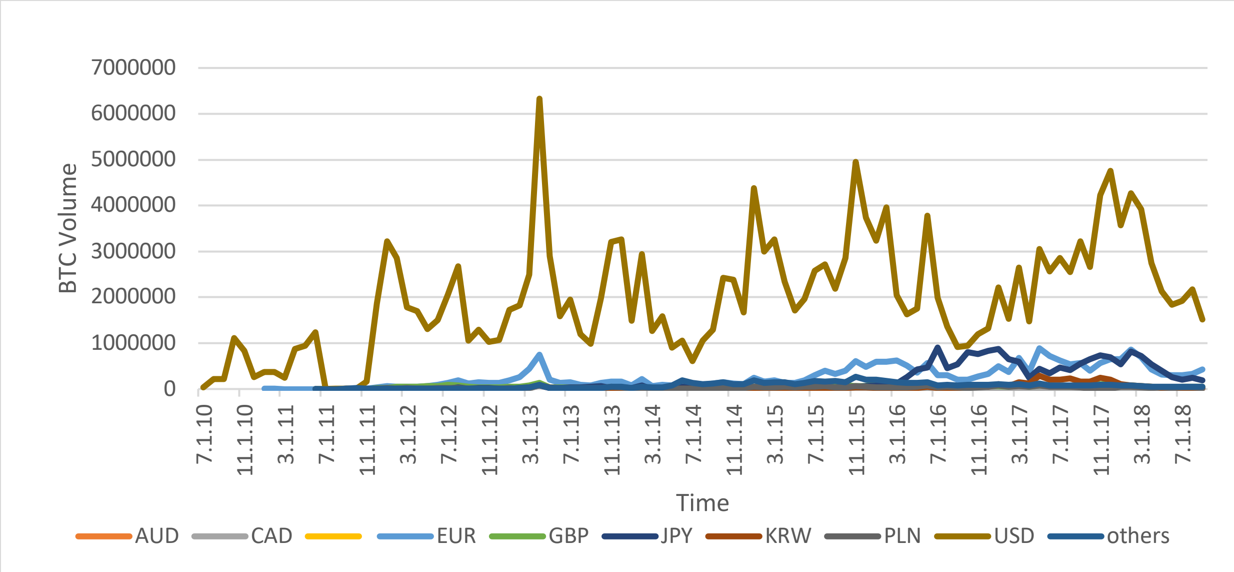


Figure 3: Bitcoin trading volume when CNY excluded

The first cluster of external variables gives a clue about a country's overall economy is the exchange rate which is a common practice in the academic literature. It is used to explain the volatility of Bitcoin in three major currencies. The data is retrieved from Datastream of Thomson Reuters.

The second cluster is stock markets as proxies of the uncertainty around political and government announcement events. S&P 500 (US), Shanghai Composite Stock Exchange (China), FTSE 100 (England), CAC 40 (France) and DAX (Germany) provide a measure of uncertainty in markets. The advantage of using stock market index is directly observable and sensitive to all events in particular economic and political ones. Because they indicate that investors' anticipations for the future whether there are optimistic or pessimistic prospects in the markets. To examine investors' behavior, some certain events are selected that might influence the Bitcoin network and hence lead to price corrections indicated by abnormal returns in the exchange rates (Glaser et al. 2014). The data is downloaded from DataStream of Thomson Reuters. In addition, another market index which is created specifically for the research is CRX100. This index samples the biggest 100 cryptocurrencies in terms of their market capitalizations. The aim of adding this variable is to capture how the entire market is affected besides Bitcoin while financial markets fluctuate. After the data transformation section, the building of the index process is explained detailed in "Additional Explanatory Variable" part.

Daily USD price per ounce of gold is a variable included because of showing similarities with Bitcoin regarding its properties. Even though Bitcoin is a much more volatile asset than gold, they are both limited resource and not linked to any underlying asset. Dyhrberg (2016) found that hedging capability of Bitcoin as gold against stock markets and US dollar by reducing market-specific risk. Data is obtained from Quandl published by World Gold Council and included the information on the trading prices on all major gold trading countries.

All the macroeconomic and financial explanatory variables have missing observations due to markets are closed over the weekend and holidays.

As an internal explanatory variable that comes from the technical ecosystem of Bitcoin is “Unique Addresses” used per day that is payment addresses and have a non-zero balance. Each address represents an account in the network. Because one person can have more than one address, this might not be a perfect stand-in for the number of users. But the fact remains that the more unique addresses, the more users as the Bitcoin market grows. These addresses are used as a proxy for the number of current users and way of expressing the daily use of the Bitcoin Network. The daily data is downloaded from Quandl.

Another explanatory variable of Bitcoin is “Trading Volume” that is the amount of the traded Bitcoin in 24 hours is obtained from Quandl. Data shows the USD trade volume from the top exchanges. Trading volume is an important metric when analyzing cryptocurrencies and it accommodates with showing a Bitcoin’s direction and movement. Essentially, volume emphasizes how many people are buying and selling the currency. This variable indicates that whether Bitcoin’s recent swings are an aberration or norm. If Bitcoin shows a high volume, it may not require attention in case of high frequent strong movements. But, if the volume decreases sharply, potential trading signals that there may be a significant reason behind this move and requires an analysis. In this study, some certain events are analyzed as the reason for these movements in the political environments. The advantage of daily trading data over weekly data is allowing to read trends that a massive trading day which is not likely to repeat and specific to those days. In order to provide a sense of scale, while Bitcoin is traded around $3.6 billion in a day, as the price hit an all-time high, Apple is traded almost $4 billion in a day in volume throughout 2017.

The last explanatory variable is “Transaction Volume” that is the aggregate number of daily confirmed Bitcoin transactions. Transaction volume shows that how many times Bitcoin has been exchanged to purchase goods and services in a day. It does not include the trading transactions. This variable might create some endogeneity in the model. However, it serves to capture another measurement which is the number of buying goods and services that trade amount, it is added in the model. The ratio graph is represented in Figure 4. It is calculated with the following equation $\frac{Traded\ Volume}{Transaction\ Volume}$. Transaction volume is another metric that is indicative of price direction. If the price of Bitcoin increases, and so are the number of transactions or vice versa. This same direction movement might suggest simultaneity that is common in financial and macroeconomic series. To avoid omitting relevant variable Bitcoin issue which causes more significant problems, the possible simultaneity is ignored and reduced by taking lag version. Before 2017, Bitcoin’s daily transaction volume was $100 million and even lower, and in 2017 Bitcoin’s USD transaction volume skyrocketed as Bitcoin’s price went up by order of magnitude. In December 2017 and January 2018, Bitcoin volumes exceeded $5 billion on some days and averaged $4 billion for about a month. The data is retrieved from bitcoinity.org.

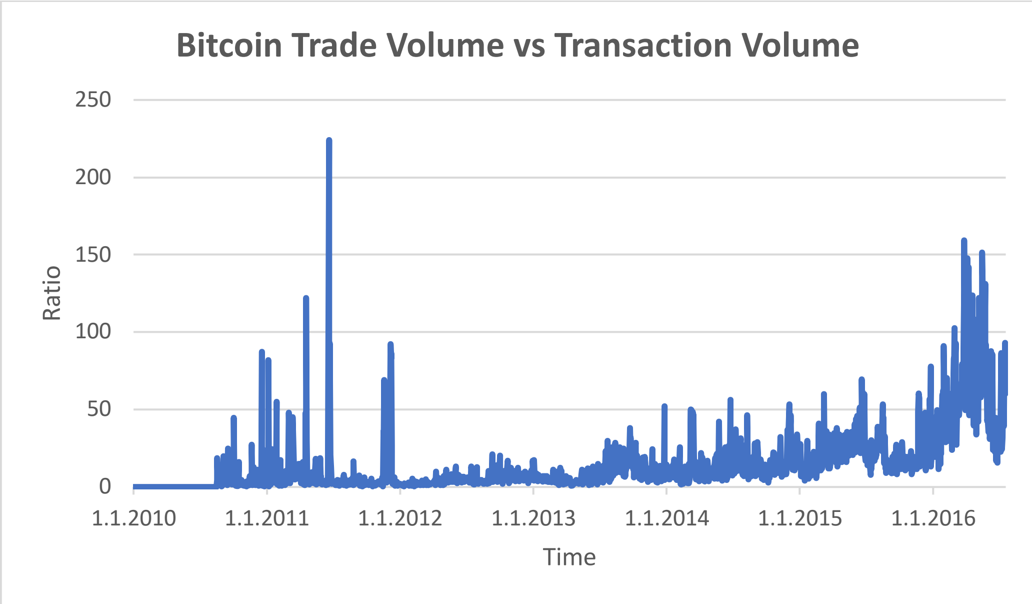


Figure 4: Trade Volume/Transaction Volume (source: Quandl)

Table reports all the dependent and independent variables and their data sources.

Table 1. Variables & Data Resources

Variables	Definitions	Data Resources
The Dependent Variable	Bitcoin Daily Return	CoinDesk (www.coindesk.com/price/)
Trading Volume	Amount of Bitcoin traded in USD	Quandl
Unique Addresses	Number of Single Accounts	Quandl
Transaction Volume	Number of Transactions	Bitcoinity.org
EUR/USD	Euro Exchange Rate Denominated in US dollar	DataStream of Thomson Reuters
GBP/USD	British Pound Exchange Rate Denominated in US dollar	DataStream of Thomson Reuters
CNY/USD	Chinese Yuan Exchange Rate Denominated in US dollar	DataStream of Thomson Reuters
S&P500	American Stock Market	DataStream of Thomson Reuters
FTSE100	London Stock Exchange	DataStream of Thomson Reuters
DAX	Frankfurt Stock Exchange	DataStream of Thomson Reuters
CAC40	French Stock Market	DataStream of Thomson Reuters
SSE	Shanghai Stock Exchange	DataStream of Thomson Reuters
Gold	USD Price per Ounce	World Gold Council (Quandl)
Events (2016– 2017) (Event Dummies)	Trump' s Victory, 20 January 2017 Brexit, 23 June 2016 German Election, 24 September 2017 French Elections, 23 April 2017 Illegalization of Bitcoin in China, 15 September 2017	

Data Transformation

In this section, the requirements of the methodology and the process of transforming the data are explained with their equations. Transformation of the data is required; hence, it can be used properly in the analysis. Otherwise some violations of the assumptions that are needing to hold. These issues make the results biased and the predictions inaccurate. First, this analysis requires stationary data. Time-series data usually presents non-stationarity a result of long-term and periodical factors. Both dependent and independent variables are non-stationary in log-levels as indicated by standard unit root tests. Thus, all series are I(1) in the beginning; they are all obtained as I(0). The time series of Bitcoin price data shows a clear upward trend over time illustrated in Figure 5. In addition to that, there are many outliers and skewness when taking the first difference of the series. As a result, this violates the validity of OLS with heteroscedasticity. For daily Bitcoin price, log returns are obtained by using the first-differences of the natural logarithm of two consecutive prices in percentage. In this way, the data is normalized and normally distributed, and the issue of outliers are overcome. A symmetric distribution in price changes is captured, distribution in daily log returns is illustrated in Figure 7. Returns are used because the distribution of daily closing price in USD in Figure 5 shows an explicit upward trend means that there is exponential growth. This form of data does not provide a meaningful sample statistic such as means, variances, and correlations with other variables. When the variables are not stationary in the regression, R-square values and t-statistics no longer follow the usual distributions and can be inflated excessively. The results are remarkable, R-squared values are commonly 0.999 and the null hypothesis testing that coefficient is always significant at 1% level if time series regressions are based on the Gauss-Markov method. The regression becomes spurious regression with non-stationary variables. However, by taking log return, the trend is removed, and therefore price moves up and down by the same multiple. This transformation makes the data stationary and remedies the heteroscedasticity problem. Only if the series is stationary, such statistics that are all constant over time are useful as the indicators of future behavior. Following Equation 1 shows the method of obtaining the logarithmic return of Bitcoin prices.

$$return_t = \log\left(\frac{price_t}{price_{t-1}}\right) \quad (1)$$

where,
$return_t$ is log returns at day t
$price_t$ is the price of Bitcoin in USD at day t

Figure 5: BTC/USD time-series in logarithmic scale for given period 2010-2018

Before the transformation, the Bitcoin daily price plot is shown in Figure 5. There is explicit evidence of an upward trend.

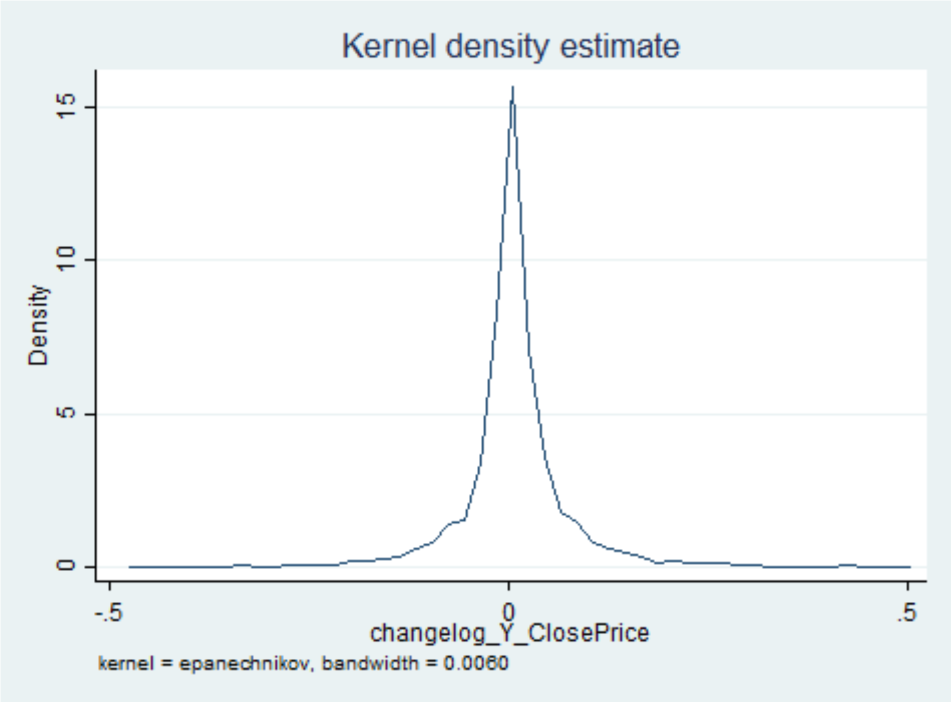


Figure 6: The distribution of the corresponding daily logarithmic returns

Figure 6 exhibits that the extreme events with the enormous density and magnitude of returns. As observed in Figure 2, the main trading inflow is expected to come from Chinese foreign exchange markets.

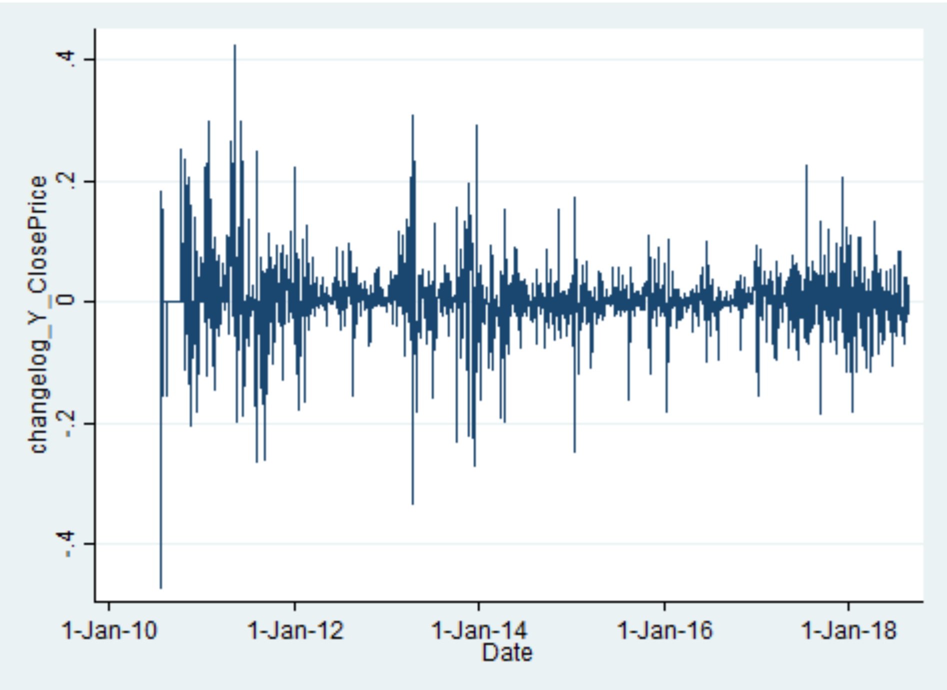


Figure 7: Daily log returns of Bitcoin price for given period 2010-2018

All log returns of EUR/USD, GBP/USD and CNY/USD are illustrated in Figure. They are calculated by the following equations.

$$returnEUR_t = \log\left(\frac{EUR_t}{EUR_{t-1}}\right) \quad (2)$$

where $returnEUR_t$ is log return at day t, EUR_t is the exchange rate of Euro denominated in US dollar, and EUR_{t-1} is the rate from one previous period.

$$returnGBP_t = \log\left(\frac{GBP_t}{GBP_{t-1}}\right) \quad (3)$$

where $returnGBP_t$ is log return at day t, GBP_t is the exchange rate of British Pound denominated in US dollar, and GBP_{t-1} is the rate from one previous period.

$$returnCNY_t = \log\left(\frac{CNY_t}{CNY_{t-1}}\right) \quad (4)$$

where $returnCNY_t$ is log return at day t, CNY_t is the exchange rate of Chinese Yuan denominated in US dollar, and CNY_{t-1} is the rate from one previous period.

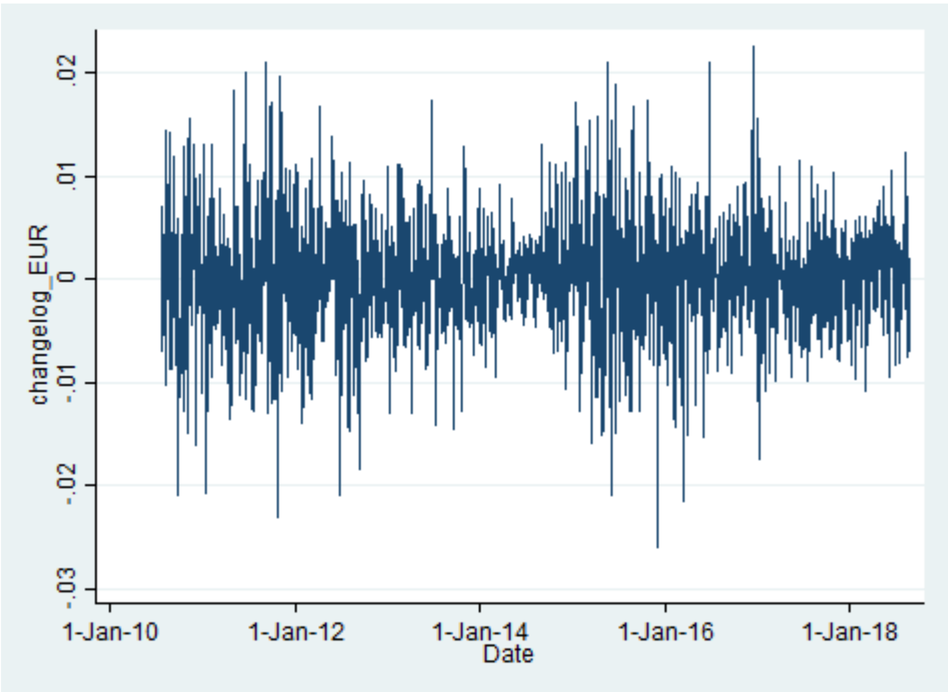


Figure 8: Daily log returns of EUR denominated in USD

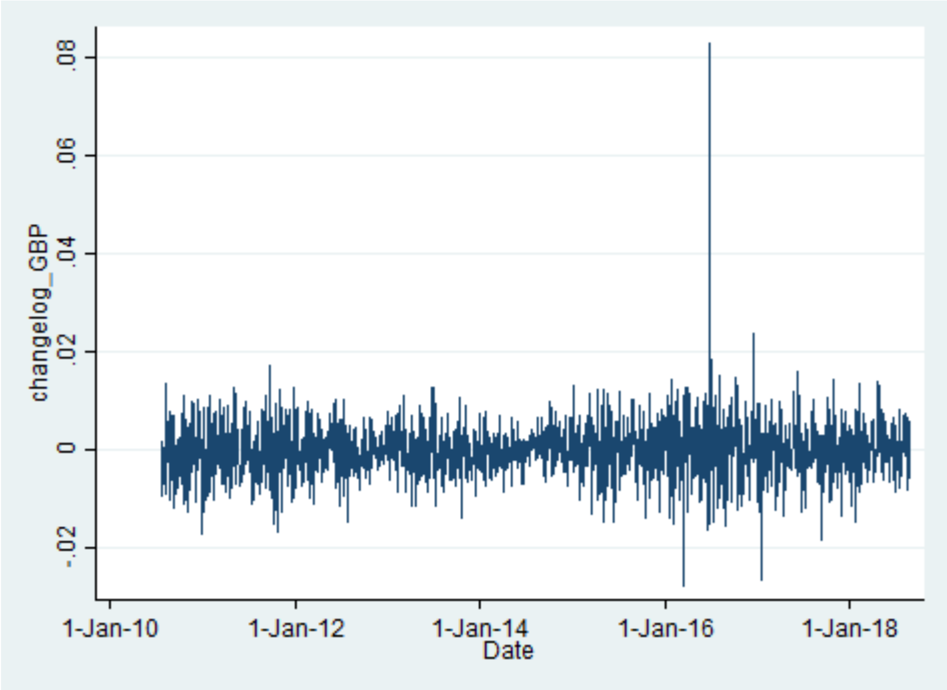


Figure 8: Daily log returns of GBP denominated in USD

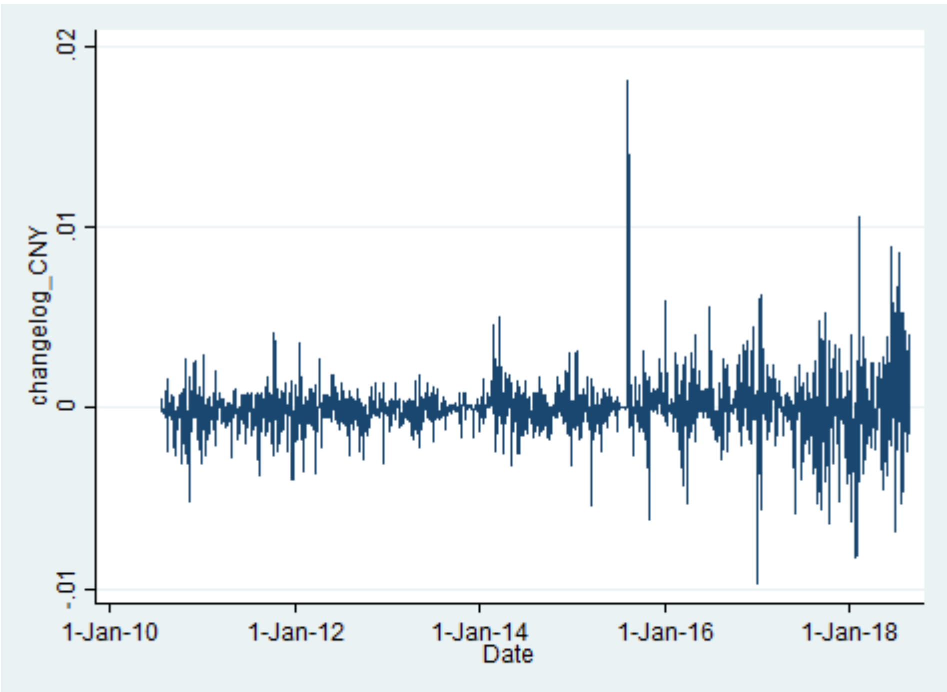


Figure 9: Daily log returns of CNY denominated in USD

All technical and financial explanatory variables' daily logarithm are taken for further analysis with the same concept. The same transformation method is applied to the daily frequencies of unique addresses, trading volume, transaction volume, S&P500, FTSE100, CAC40, SSE, and Gold. To find the price changes, the values at a given time t are divided by $t-1$ since the natural logarithm cannot be taken if the values are negative. If t is subtracted by $t-1$, there would be many negative values. The transformation that is normalization process allows to study with the same metric through variables and make the results between variables more accurate and informative. Briefly, in this part, the regression model is adapted to time series data assuming that the variables in the regression are all stationary. Besides, all the initial time series of the explanatory variables before transformation and after the conversion can be found in Appendix Figures 2(A). (a) plots represent non-stationary data. (b) plots represent stationary forms.

Summary Statistics

The descriptive statistics for the original dependent and independent daily data are represented in Table 2. All variables are highly volatile between the minimum and maximum values. Bitcoin exhibits common features with the traditional financial assets which are sensitive to shocks, non-stationary and having an upward trend. The correlation matrix is shown in Table 3.

Table 2

Summary Statistics of Original Variables

Variable	N	Mean	SD	Min	Max
Bitcoin Price	2,117	1376.2	2899.5	0.05	18960.52
Unique Address	2,117	221535	211593.6	284	1072861
Trade Volume	2,117	112000000	332000000	0	4550000000
Transaction Volume	2,117	118572.6	106312	278	490644
Gold OZ(USD)	2,117	1358.8	186.6	1049.4	1895
CNY/USD	2,117	6.4192	0.2387	6.0412	6.9557
EUR/USD	2,117	0.8122	0.0754	0.6715	0.96358
GBP/USD	2,117	0.6716	0.0635	0.5824	0.82888
S&P500	2,117	1867.8	479.5	1047.2	2897.52
CAC40	2,117	4301.7	697.5	2781.7	5640.1
DAX	2,117	9384.9	2247.3	5072.3	13559.6
FTSE100	2,117	6470.9	667.2	4944.4	7877.45
SSE	2,117	2912.9	601.2	2040.7	5410.859

Table 3

Correlation matrix between variables

		1.	2.	3.	4.	5.	6.	7.	8.
1.	Bitcoin Price	1.00							
2.	Unique Address	0.67*	1.00						
3.	Trade Volume	0.86*	0.57*	1.00					
4.	Transaction Volume	0.57*	0.97*	0.47*	1.00				
5.	Gold	-0.20*	-0.56*	-0.13*	-0.55*	1.00			
6.	CNY/USD	0.19*	0.51*	0.14*	0.55*	-0.21	1.00		
7.	EUR/USD	0.19*	0.73*	0.13*	0.78*	-0.60*	0.46*	1.00	
8.	GBP/USD	0.47*	0.83*	0.36*	0.87*	-0.37*	0.73*	0.75*	1.00
9.	S&P500	0.69*	0.89*	0.53*	0.87*	-0.62*	0.25*	0.66*	0.71*
10.	CAC40	0.62*	0.82*	0.48*	0.79*	-0.73*	0.29*	0.62*	0.62*
11.	DAX	0.62*	0.88*	0.48*	0.86*	-0.69*	0.26*	0.70*	0.68*
12.	FTSE100	0.63*	0.77*	0.46*	0.75*	-0.57*	0.18*	0.49*	0.64*
13.	SSE	0.30*	0.56*	0.26*	0.55*	-0.52*	0.38*	0.68*	0.49*

Note: *p<.05

		9.	10.	11.	12.	13.
9.	S&P500	1.00				
10.	CAC40	0.93*	1.00			
11.	DAX	0.97*	0.97*	1.00		
12.	FTSE100	0.92*	0.91*	0.93*	1.00	
13.	SSE	0.53*	0.65*	0.62*	0.42*	1.00

Note: *p<.05

As it is observed that all variables are highly significant and correlated in Table 2 and Table 3 respectively. This result is usually expected since time series data show high inter-correlation even though there is not. This inflated correlation is attributed to trend in time series.

Additional Explanatory Variable

In this part, an additional independent variable is introduced to build an alternative model. The idea of this section is to study crypto market aggregated by building an index considered as a financial market index following Sovbetov's (2018) research. By adding this variable, if there is a relationship between Bitcoin price and the entire cryptocurrency market. In another way, whether the crypto market can explain the changes in Bitcoin price and predict. Even though the Index is conducted as a side project, it provides insight into Bitcoin's movement correspondingly the crypto market.

It is important to mention that Bitcoin also contributes to this index. Including Bitcoin seems that it becomes an endogenous variable. On the other hand, excluding Bitcoin from the index means omitting a relevant variable which is also the most significant contributor in the market. To mitigate the endogeneity problem, a hundred cryptocurrencies are collected. The rest of the cryptocurrencies except Bitcoin represent the 51% of the index. The market capitalization of the crypto market is not incorporated as a variable in the regression. It is used for the only providing an overview purpose to the market.

Building Crypto 100 Index

A cryptocurrency index to conduct this research by sampling top 100 crypto coins which have the most contribution to market capitalization weights. These 100 largest market cap cryptocurrencies are the proxy for the entire market in 2018 (1658 cryptocurrency). Crypto 100 index (CRX100) is built with volume and volatility in the aim of using in the analysis as statistical data. The objective is to take a glance at the price movements of the crypto market as a whole. Some market factors are downloaded from coinmarketcap.com which are market capitalization, trading volume, opening price, closing price, high and low intraday price for 100 cryptocurrencies each. After that, some market factors are derived that are total market capitalization, volume and volatility to use as explanatory variables in an attempt to compare with stock markets behavior such as S&P500 and assess how far cryptocurrency market from conventional stock markets regarding volatility. To conduct this part, Sovbetov (2018)'s study is taken as a starting point. However, this research takes a step further the previous research by expanding the number of cryptocurrencies up to the largest 100 from 50 largest ones concerning their market capitalizations. According to total capitalization on 28 August 2018, they compose %90.62 of the entire market. While first five largest cryptocurrency forms %73.70 of the whole market, 49.86%, 12.23%, 5.61%, 3.96%, and 2.04% belong to Bitcoin, Ethereum, Ripple, Bitcoin Cash, and EOS, respectively. A pie chart shows distributions of 5 largest and others can be seen in *Chart 1* in the Appendix.

Another differentiating point from Sovbetov (2018)'s study is that the market capitalization of Bitcoin not included in the analysis. Market capitalization may not be an accurate way to describe the total value of Bitcoin. This metric has some significant limitations in determining the actual worth of Bitcoin. Cryptocurrencies' market cap value does not mean that it has flown into those. This measure might give an exaggerated impression of Bitcoin's relative size. In addition to that, due to the nature of Bitcoin, there is a non-tradable portion that is not quantified in the total supply. The reason is that there are investors who are not able to access their digital wallets or lost their account for good. According to the Blockchain intelligence platform (Chainalysis) research in the last quarter of 2017, the estimation range of the lost Bitcoin is between 3.79 million and 2.78 million based on the high and low assumption respectively. They are prevented from trading due to the strict structure of Bitcoin. This structure is provided by Blockchain where all transactions are recorded without any deviation. Because this portion of non-tradable disposal Bitcoins causes bias, market capitalization data is not included in the data. But it is used to provide an insight into the market as a fraction. The method that is used to build index can be followed step-by-step:

1) Sample the largest 100 cryptocurrencies from coinmarketcap.com. The list of 100 cryptocurrencies can be found in Currency List of the CRX100 Index in the Appendix.

Because rankings may vary over time, it requires to mention which cryptocurrencies compose the index. The index is created in the third quarter of 2018.

2) Sum all 100 cryptocurrencies' market capitalizations to reach the total market cap.
3) Calculate the weight of each cryptocurrency based on their market capitalization by using the formula below for both high and low price for each coin, separately. Market caps of the currencies are depicted in Chart 1(A) in the Appendix.

$$\text{CRX 100 Index Price} = \sum_{i=1}^{100} P_{i,t} \frac{MC_{i,t}}{MC_{CRX100,t}}$$

where, $MC_{i,t}$ is the market cap, $P_{i,t}$ is price and $MC_{CRX100,t}$ is the total market cap of 100 currencies.

4) Sum both high and low price of all currencies.
5) Sum trading volume of 100 currencies. This step is performed to provide insight into the cryptocurrency market. Trading Volume of CRX100 is shown in Chart 2(A) in the Appendix. The formula is below.

$$\text{Crypto 100 Index Volume} = \sum_{i=1}^{100} VOL_{i,t}$$

6) Derive daily volatility of CRX100 Index to visualize the fluctuations over time using the formula below.

$$Crypto\ 100\ Index\ Volatility = \ln\left(\frac{P_{h,t}}{P_{l,t}}\right)$$

Where $P_{h,t}$ is the highest price of CRX100 index recorded at day t, $P_{l,t}$ is the lowest prices of index recorded at day t. Figure 10 represents the daily volatility of the cryptocurrency market as follows:

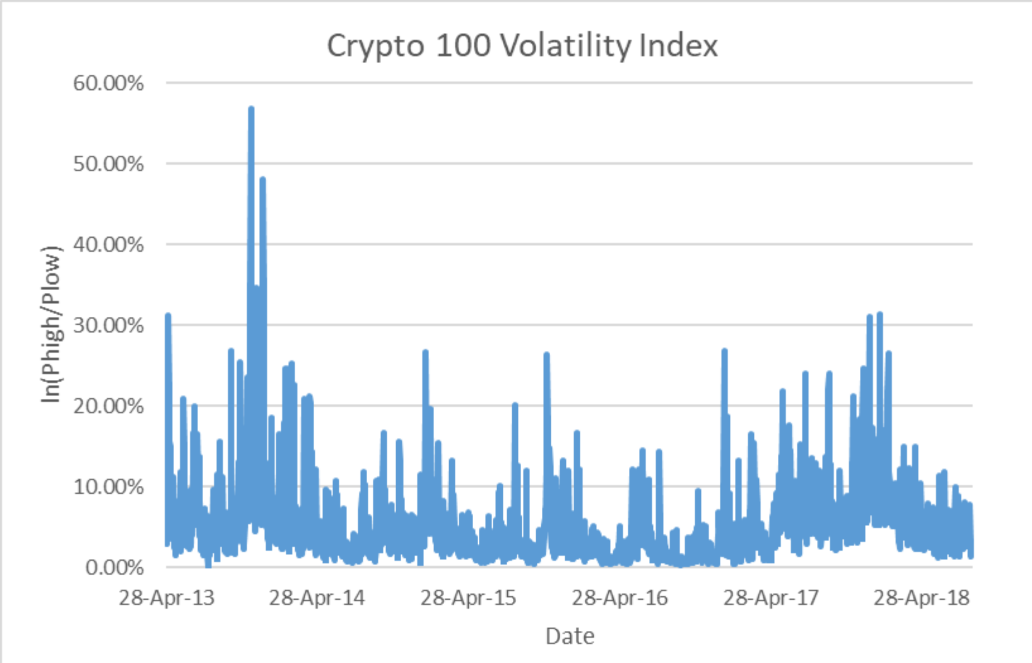


Figure 10: Crypto 100 Volatility Index in USD

7) Take the average of $P_{l,t}$ and $P_{h,t}$ of CRX100 index recorded at day t to include into the model as the daily price observation of the cryptocurrency market.

$$Crypto\ 100\ Price = \mu\ (P_{h,t,}P_{l,t})$$

Logarithmic returns of CRX100 is shown in Figure 11.

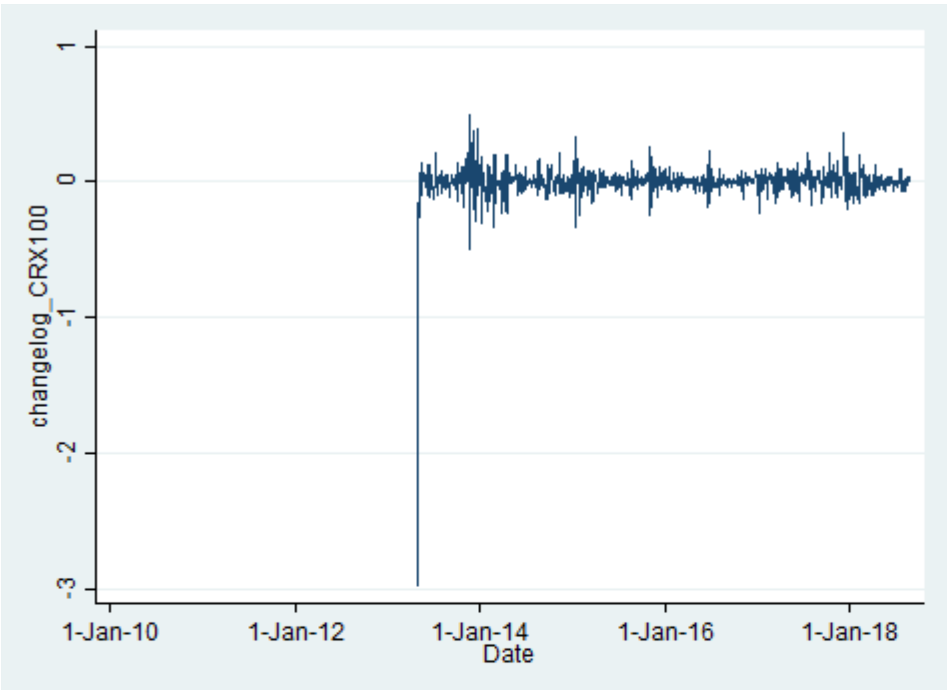


Figure 11: Daily log returns of CRX100 in USD

Summary Statistics

The descriptive statistics CRX100 Index as an additional explanatory variable included in the model are represented for the daily data in Table 4. The correlation matrix included CRX100 is presented in Table 5.

Table 4

Summary Statistics included CRX100 Index

Variable	N	Mean	SD	Min	Max
Bitcoin Price	2,117	1376.2	2899.5	0.05	18960.52
Unique Address	2,117	221535	211593.6	284	1072861
Trade Volume	2,117	112000000	332000000	0	4550000000
Transaction Volume	2,117	118572.6	106312	278	490644
CRX100	**1,392**	**1173.4**	**1652.7**	**61.457**	**14700.14**
Gold OZ(USD)	2,117	1358.8	186.6	1049.4	1895
CNY/USD	2,117	6.4192	0.2387	6.0412	6.9557
EUR/USD	2,117	0.8122	0.0754	0.6715	0.96358
GBP/USD	2,117	0.6716	0.0635	0.5824	0.82888
S&P500	2,117	1867.8	479.5	1047.2	2897.52
CAC40	2,117	4301.7	697.5	2781.7	5640.1
DAX	2,117	9384.9	2247.3	5072.3	13559.6
FTSE100	2,117	6470.9	667.2	4944.4	7877.45
SSE	2,117	2912.9	601.2	2040.7	5410.859

It can be seen that the cryptocurrency market as a whole also shares common features with the traditional stock markets regarding high volatility between the minimum and maximum observations. However, cryptocurrency market is still embryonic relative to the stock markets. Hence, the standard deviation is very close to the mean indicates that huge price movements. It can be observed from the gap between minimum and maximum. This spread can provide a hint about how cryptocurrency market is risky and young relative to traditional financial markets.

Table 5

Correlation matrix between variables

		1.	2.	3.	4.	5.	6.	7.	8.
1.	Bitcoin Price	1.00							
2.	Unique Address	0.67*	1.00						
3.	Trade Volume	0.86*	0.57*	1.00					
4.	Transaction Volume	0.57*	0.97*	0.47*	1.00				
5.	Gold	-0.20*	-0.56*	-0.13*	-0.55*	1.00			
6.	CNY/USD	0.19*	0.51*	0.14*	0.55*	-0.21	1.00		
7.	EUR/USD	0.19*	0.73*	0.13*	0.78*	-0.60*	0.46*	1.00	
8.	GBP/USD	0.47*	0.83*	0.36*	0.87*	-0.37*	0.73*	0.75*	1.00
9.	S&P500	0.69*	0.89*	0.53*	0.87*	-0.62*	0.25*	0.66*	0.71*
10.	CAC40	0.62*	0.82*	0.48*	0.79*	-0.73*	0.29*	0.62*	0.62*
11.	DAX	0.62*	0.88*	0.48*	0.86*	-0.69*	0.26*	0.70*	0.68*
12.	FTSE100	0.63*	0.77*	0.46*	0.75*	-0.57*	0.18*	0.49*	0.64*
13.	SSE	0.30*	0.56*	0.26*	0.55*	-0.52*	0.38*	0.68*	0.49*
14.	CRX100	0.97*	0.66*	0.86*	0.53*	0.21*	0.26*	-0.004	0.39*

Note: *p<.05

		9.	10.	11.	12.	13.	14.
9.	S&P500	1.00					
10.	CAC40	0.93*	1.00				
11.	DAX	0.97*	0.97*	1.00			
12.	FTSE100	0.92*	0.91*	0.93*	1.00		
13.	SSE	0.53*	0.65*	0.62*	0.42*	1.00	
14.	CRX100	0.76*	0.65*	0.66*	0.64*	0.19*	1.00

Note: *p<.05

Methodology

This section provides the methodology used to examine the main question of this research. Multivariate time series regression analysis is used to find relationship between the dependent and the independent variables. The daily Bitcoin return is the dependent variable. The initial step of the analysis is whether the independent variables can explain the price changes in Bitcoin by using the daily descriptive model. Then, the daily predictive model is built to study whether the explanatory variables are able to predict the price changes of Bitcoin. In order to do this, OLS regression is used. The next step continues with studying on the volatility of Bitcoin price which indicates the ARCH/GARCH model. The entire analysis is conducted on the daily basis data. While it is run with both CRX100 Index is included and not included separately at the first part where OLS is performed, it is conducted only with the included version. All variables are run in their logarithmic transformed forms to satisfy the stationary condition. Hence, the actual effect of the independent variables on the Bitcoin price changes can be investigated if time series are de-trended. Otherwise, the price changes and explanatory variables may show a strong relationship when there is not. The regression outputs are run by testing heteroscedasticity in the residuals, and robust standard errors are applied. It is a prevalent practice to do this in case of large number observations.

Bitcoin Return

In this part, the daily price change of Bitcoin is studied. The daily return is the dependent variable.

Daily Descriptive Model

Explanatory variables are tested if they can explain the daily Bitcoin price changes. The intention to follow this step is to find out whether the recent returns can be an efficient proxy. It is tested that if the regression model is sufficient at predicting the present since the financial time series often has strong contemporaneous correlations. The regression model is shown as:

$$return_t = a_0 + \beta_1 Addresses_t + \beta_2 TradVol_t + \beta_3 TransVol_t + \beta_4 Gold_t + \beta_5 CNY_t + \beta_6 EUR_t + \beta_7 GBP_t + \beta_8 SP500_t + \beta_9 CAC40_t + \beta_{10} DAX_t + \beta_{11} FTSE100_t + \beta_{12} SSE_t + \mathcal{E}_t \qquad (5)$$

where,

$return_t$: the dependent variable represents the daily Bitcoin price changes at day t
$Addresses_t$: unique addresses at day t represent Bitcoin users
$TradVol_t$: trading Volume in USD at day t
$TransVol_t$: number of transactions confirmed at day t
$Gold_t$: Gold price per ounce at day t
CNY_t: Chinese Yuan exchange rate against US dollar at day t
EUR_t: Euro exchange rate against US dollar at day t
GBP_t: British Pound exchange rate against US dollar at day t
$SP500_t$: US stock market price index at day t
$CAC40_t$: French stock market index at day t
DAX_t: German stock market index at day t
$FTSE100_t$: British stock market index at day t
SSE_t: Shanghai stock market index at day t
$\mathcal{E}_t$: error term
a_0: constant term

The output of the model (3) is displayed in Table 6. All variables are insignificant means that explanatory variables included in the model cannot explain the Bitcoin return. In other words, no contemporaneous effect is found.

Table 6

Regression results of the descriptive model tested with the different variable contribution

	Coefficients	Standard Errors
Unique Address	0.00273	0.01205
Trade Volume	0.00064	0.00306
Transaction Volume	0.01534	0.00799
Gold	0.36883	0.23163
CNY/USD	0.85454	0.82472
EUR/USD	-0.15259	0.35400
GPB/USD	0.21207	0.29173
S&P500	0.31862	0.29178
CAC40	0.00613	0.33497
DAX	0.32513	0.32881
FTSE100	-0.35180	0.33019
SSE	0.03811	0.11347
Constant	0.00523***	0.00138
N observations	2,095	
Prob > F	0.4484	
R^2	0.0096	

Note: *p<.05, **p<.01, ***p<.001

Daily Predictive Model

The independent variables are tested whether they can predict the returns as the following model:

$$return_t = a_0 + \beta_1 Addresses_{t-1} + \beta_2 TradVol_{t-1} + \beta_3 TransVol_{t-1} + \beta_4 Gold_{t-1} + \beta_5 CNY_{t-1} + \beta_6 EUR_{t-1} + \beta_7 GPB_{t-1} + \beta_8 SP500_{t-1} + \beta_9 CAC40_{t-1} + \beta_{10} DAX_{t-1} + \beta_{11} FTSE100_{t-1} + \beta_{12} SSE_{t-1} + \varepsilon_t \qquad (6)$$

where,

$return_t$: the dependent variable represents the daily Bitcoin price changes at day t

$Addresses_{t-1}$: unique Addresses at day $t-1$ represent Bitcoin users

$TradVol_{t-1}$: trading Volume in USD at day $t-1$

$TransVol_{t-1}$: number of transactions confirmed at day $t-1$

$Gold_{t-1}$: Gold price per ounce at day $t-1$

CNY_{t-1}: Chinese Yuan exchange rate against US dollar at day $t-1$

EUR_{t-1}: Euro exchange rate against US dollar at day $t-1$
GBP_{t-1}: British Pound exchange rate against US dollar at day $t-1$
$SP500_{t-1}$: US stock market price index at day $t-1$
$CAC40_{t-1}$: French stock market index at day $t-1$
DAX_{t-1}: German stock market index at day $t-1$
$FTSE100_{t-1}$: British stock market index at day $t-1$
SSE_{t-1}: Shanghai stock market index at day $t-1$
ε_t: error term
a_0: constant term

Lagged versions of the explanatory variables are created to run this model (4). This model allows predicting the future by taking the current varying values. The results are summarized in Table 7. All variables are insignificant except Gold and FTSE100. This output shows a relationship between Gold and the British stock market and the future Bitcoin returns. While there is a positive relationship with Gold, negative correlation with FTSE100. Due to similar properties of Bitcoin and Gold may give the same direction in the movement in case of inflow into the Gold. They are similar resources that are both limited and not back any underlying asset. R-squared shows that the predictive model (4) can explain only 1.01% of the variation in Bitcoin return.

Table 7

Regression results of the predictive model tested with the different variable contribution

	Coefficients	Standard Errors
Unique Address_t-1	-0.01822	0.01152
Trade Volume_t-1	-0.00020	0.00239
Transaction Volume_t-1	0.00245	0.00929
Gold_t-1	0.47832**	0.17559
CNY/USD_t-1	1.10420	0.77900
EUR/USD_t-1	0.19666	0.37496
GPB/USD_t-1	0.00084	0.30012
S&P500_t-1	0.20773	0.25480
CAC40_t-1	-0.27191	0.33234
DAX_t-1	0.55560	0.31728
FTSE100_t-1	-0.64767*	0.30384
SSE_t-1	0.04840	0.08783
Constant	0.00543***	0.00139
N observations	2,094	
Prob > F	0.0757	
R^2	0.0101	

Note: *p<.05, **p<.01, ***p<.001

Brexit Effect on the Financial Markets

The regression results show that the stock prices of FTSE100 from one previous period have a significant effect on the Bitcoin returns today. The negative relationship with FTSE100 may come from investors who trade in British stock exchange may see Bitcoin as an alternative investment against the stock market. This outcome may be attributable to Brexit that England's leaving decision of EU in March 2017. There are some potential discussions about how Brexit causes the surge in Bitcoin price. It is undeniable that it creates big uncertainties in the political and financial environments. The UK withdrawal from EU and the no-deal period lead to several consequences such as resigning of the government members, disagreement in policies or uncertainty in licenses for financial services. One potential catalyst for adoption of the Bitcoin and hence, increasing in price may be the possibility of lost British bank accounts in EU zone. British residents who live in outside of Britain but in Europe may not be able to access their accounts anymore. This population is approximately 1 million at the beginning of 2017 to the report published by UK National Statistics Office. Another important point to highlight is the potential uncertainty in Pound and the other currencies affected like Euro and Swiss Franc. According to the Global Council's report (2016), ten years of uncertainty in particular in Pound is predicted. When there are doubts about fiat currencies, people invest their money in alternative assets such as gold. Bitcoin may act as safe-haven among British investors in case of an expected high volatility in Pound. The outputs of the regression signal that the investors treat Bitcoin as a new alternative asset. The Bitcoin price sunk can be observed in Chart 2 when UK referendum results announced in 23rd June 2016. The plummet in the chart corresponds the announcement date exactly. After that, the value rises. This rise follows a decreasing trend in the value again.

Chart 2: Bitcoin price in USD around the UK referendum result announcements

Bitcoin Return Model with CRX100 Index

This section studies which variables explain and predict daily returns when Crypto 100 Index is included into the multivariate regression analysis. The index is used as a proxy for the crypto market such as the other financial markets and indicates that if there is a relationship with Bitcoin daily return. It is also converted to a stationary through the first differencing method.

It is important to mention that CRX100 index includes Bitcoin. To include Bitcoin daily price data on both side of regression might create endogeneity in the following descriptive model. However, the predictive model reduces this simultaneity issue by adding a lagged variable.

Daily Descriptive Model

The model is described as following:

$$return_t = a_0 + \beta_1 Addresses_t + \beta_2 TradVol_t + \beta_3 TransVol_t + \beta_4 Gold_t + \beta_5 CNY_t + \beta_6 EUR_t + \beta_7 GPB_t + \beta_8 SP500_t + \beta_9 CAC40_t + \beta_{10} DAX_t + \beta_{11} FTSE100_t + \beta_{12} SSE_t + \beta_{13} CRX100_t + \mathcal{E}_t \qquad (7)$$

The results of the regression model (5) are shown in Table 8. All variables are insignificant to explain Bitcoin return except CRX100 Index. There is a positive relationship with the return. This is an expected outcome since all altcoins' movements are highly linked to Bitcoin.

Table 8

Regression results of the descriptive model tested with the different variable contribution

	Coefficients	Standard Errors
Unique Address	-0.00572	0.01200
Trade Volume	-0.00033	0.00277
Transaction Volume	0.01803	0.01443
Gold	0.04415	0.17657
CNY/USD	-0.03468	0.71571
EUR/USD	-0.08925	0.35847
GPB/USD	0.09189	0.25439
S&P500	-0.05076	0.28476
CAC40	0.06693	0.33595
DAX	0.17737	0.30612
FTSE100	-0.31203	0.30327
SSE	0.10407	0.10180
CRX100	0.14788*	0.06619
Constant	0.00272***	0.00132
N observations	1,391	
Prob > F	0.5412	
R^2	0.1141	

Note: *p<.05, **p<.01, ***p<.001

Daily Predictive Model

The predictive model as following:

$$return_t = a_0 + \beta_1 Addresses_{t-1} + \beta_2 TradVol_{t-1} + \beta_3 TransVol_{t-1} + \beta_4 Gold_{t-1} + \beta_5 CNY_{t-1} + \beta_6 EUR_{t-1} + \beta_7 GPB_{t-1} + \beta_8 SP500_{t-1} + \beta_9 CAC40_{t-1} + \beta_{10} DAX_{t-1} + \beta_{11} FTSE100_{t-1} + \beta_{12} SSE_{t-1} + \beta_{13} CRX100_{t-1} + \mathcal{E}_t \qquad (8)$$

Most of the variables are insignificant except Trade Volume, CNY/USD and DAX. The results are shown in Table 9. There is a significant relationship between Chinese Yuan and future Bitcoin return. While there is a positive relationship between Yuan and DAX and predicted returns, there is a negative relationship between trade volume and predicted returns. CNY/USD result may be attributed to China is the most Bitcoin traded country, and it has a major impact on future returns relative to other currencies. When the value of Chinese Yuan rises against the dollar, investors may inflow to Bitcoin at the next period since Bitcoin price decreases in US dollars against Yuan. Another result is that the negative relationship between Trading Volume and future return. Increase in trading volume shows that more people attract Bitcoin and they trade a larger amount. This leads to a rise in prices. Hence, the possible explanation is that the returns decrease when trading volume increase at the previous period. Last, there is a positive relationship between the German stock market and the future gains in Bitcoin. When the stock market rises at the last period, Bitcoin return rises at the subsequent period. Germany is the first country who formally recognize Bitcoin as legal tender in 2013. Germany's Ministry of Finance accepts that the Bitcoin as a unit of account. This recognition means that commercial transactions are subject to tax applications and some regulations. On the other hand, the government attempts to increase adoption and usage more safely. German regulators may consider Bitcoin as a potential alternative to Euro. After this decision, German investors' optimistic expectations for the stock markets may reflect in the same direction as Bitcoin returns in the future. However, the model(6) can only explain 1.53% of the variation in return.

Table 9

Regression results of the predictive model tested with the different variable contribution

	Coefficients	Standard Errors
Unique Address_t-1	0.00152	0.01158
Trade Volume_t-1	-0.00554*	0.00278
Transaction Volume_t-1	-0.00986	0.01469
Gold_t-1	0.08533	0.16433
CNY/USD_t-1	1.69895*	0.74627
EUR/USD_t-1	-0.00626	0.32834
GPB/USD_t-1	0.00137	0.25908
S&P500_t-1	0.18098	0.23898
CAC40_t-1	-0.30352	0.35600
DAX_t-1	0.68739*	0.31044
FTSE100_t-1	-0.55115	0.30848
SSE_t-1	0.02957	0.08041
CRX100_t-1	0.02310	0.02358
Constant	0.00256	0.00139
N observations	1,390	
Prob > F	0.1339	
R^2	0.0153	

Note: *p<.05, **p<.01, ***p<.001

Impact of Events on Bitcoin Returns

2016 and 2017 were eventful years around the world regarding government changes, leaving EU and announcements. In 2016, while the US was shocked by Trump's victory, UK encountered with Brexit withdrawal from EU. In 2017, the important national elections occurred in Europe which may affect the political and economic scene significantly in the following years. France and Germany hold debatable elections. In addition, China declared the illegalization of Bitcoin where the most traded country. All of these events created political and economic upheavals reflect the financial markets around the world. The uncertainty in the future policies of governments implements lead to doubts about the direction of the economic situation. This doubtfulness reflects the financial markets which makes them highly volatile. Some previous studies (Dyhrberg 2015; Bouri et al. 2016; Eisl et al. 2015) investigate that the hedging capacities of Bitcoin. They find that the negative relationship with stock markets. This correlation shows that the role of Bitcoin as the portfolio diversifier. In this part, the effects of the outstanding events influenced the financial markets are tested on the Bitcoin returns. The lagged explanatory and five dummy variables are included in the regression. The model can be seen as follows:

$$return_t = a_0 + \beta_1 Addresses_t + \beta_2 TradVol_t + \beta_3 TransVol_t + \beta_4 Gold_t + \beta_5 CNY_t + \beta_6 EUR_t + \beta_7 GPB_t + \beta_8 SP500_t + \beta_9 CAC40_t + \beta_{10} DAX_t + \beta_{11} FTSE100_t + \beta_{12} SSE_t + \beta_{13} CRX100_t + TrumpWin + FrenchElec + GermanElec + Brexit + ChinaBan + \varepsilon_t \tag{9}$$

where,
$return_t$: the dependent variable represents the daily Bitcoin price changes at day t
$Addresses_{t-1}$: unique Addresses at day $t-1$ represent Bitcoin users
$TradVol_{t-1}$: trading Volume in USD at day $t-1$
$TransVol_{t-1}$: number of transactions confirmed at day $t-1$
$Gold_{t-1}$: Gold price per ounce at day $t-1$
CNY_{t-1}: Chinese Yuan exchange rate against US dollar at day $t-1$
EUR_{t-1}: Euro exchange rate against US dollar at day $t-1$
GBP_{t-1}: British Pound exchange rate against US dollar at day $t-1$
$SP500_{t-1}$: US stock market price index at day $t-1$
$CAC40_{t-1}$: French stock market index at day $t-1$
DAX_{t-1}: German stock market index at day $t-1$
$FTSE100_{t-1}$: British stock market index at day $t-1$
SSE_{t-1}: Shanghai stock market index at day $t-1$
$TrumpWin$: dummy at the day of Trump wins
$FrenchElec$: dummy at the day of French election holds
$GermanElec$: dummy at the day of German election holds
$Brexit$: dummy at the day of UK leaves EU
$ChinaBan$: dummy at the day of China illegalizes Bitcoin
ε_t: error term
a_0: constant term

The regression output is shown in Table 10.

Table 10

Regression results of the event dummy model tested with the different variable contribution

	Coefficients	Standard Errors
Unique Address	-0.01522	0.01291
Trade Volume	-0.00250	0.00330
Transaction Volume	0.00494	0.01481
CRX100	0.09674	0.05007
Gold	0.16985	0.19376
CNY/USD	-0.31905	0.79110
EUR/USD	0.00300	0.37428
GPB/USD	0.25587	0.28825
S&P500	-0.10078	0.25946
CAC40	0.26004	0.37794
DAX	0.06838	0.32230
FTSE100	-0.48957	0.33627
SSE	0.09230	0.10421
TrumpWin	0.00956*	0.0043
FrenchElec	0.00182	0.03344
GermanElec	0.00169	0.02566
Brexit	0.00940	0.01488
ChinaBan	-0.02105	0.01511
Constant	0.00085	0.00165
N observations	1,113	
Prob > F	0.2582	
R^2	0.0659	

Note: *p<.05, **p<.01, ***p<.001

As observed in the results, investors react to Trump's victory. The election of Donald Trump has a significant effect on Bitcoin price but not in the crypto market. The price raised from $709 to $739. It increased more than 4% overnight. Chart 3 depicts the price had begun surging while the votes were counting. When Trump pulled off a surprising success, the price bounced.

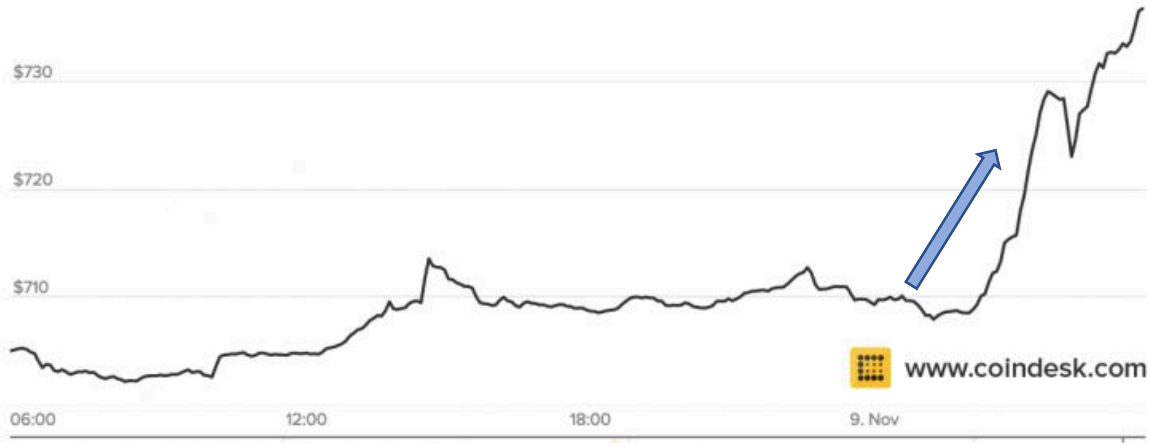


Chart 3: Bitcoin price surge after Trump win the presidential election in USD (source: coindesk)

The price jump points out that investors tend towards alternative assets outside of stocks in uncertain periods. Trump's presidency leads to expectations of the complex implementations in business and politic areas, for example, corporate tax law changes. This uncertainty concludes that when the future of the markets and countries are not predictable, people seek protection for their assets. They turn to the assets that are not correlated with traditional stocks and bonds such as gold and in recent history, Bitcoin.

From Time Series Data to OLS Regression

Time-series data usually contains memory-structure by nature. This characteristic indicates that the information in observations in the sample does not grow fast as the sample size increases to result in asymptotic convergence of estimators to the actual parameter values (Granger, 1974). Hence, the observations that are far apart in time are still strongly correlated. As a result, OLS methods contain some violations generate inaccurate and inefficient predictions. The set of sufficiency conditions serves as a checklist to identify the variables that included in the efficient model. An efficient OLS model must be developed that circumvents the violations of the assumption of independence (Pickett et al. 2005).

Time series data is a stochastic process that has a unit root that shows an unpredictable systematic pattern. This process leads to some common problems. One issue is the serial correlation that is the correlation between error terms of the subsequent periods. The standards errors become biased but not coefficients. Another issue with time series is the trend over time makes the data spurious. To address these issues, some assumptions need to hold to conduct OLS which make time series' probability distribution is stable over time; the residuals should have a constant variance throughout the series. The residuals should be normally and independently distributed. After these assumptions hold OLS is valid.

Before conducting an OLS for an analysis of Bitcoin returns, there are some assumptions require to hold if working with large time series data. OLS regression in time series allows analyzing whether independent variables can explain and predict the return of Bitcoin. Below the assumptions required to hold, and tests applied to check the validity of OLS are defined in the following:

- **Weak Exogeneity – Stationary**

The variables are stationary and weakly exogenous concerning the disturbance term. Error term at given time must be independent only from the current values but not all past and future values.

$$E\left(u_t \mid x_{t,2}, x_{t,3}, \dots, x_{t,K} \right) = 0 \qquad (10)$$

- **No Perfect Collinearity**

Any variable x is constant or stated as linear function of one other or more variables. All set of constants α_i should be zero.

$$a_1 + a_2 x_{t,2} + \cdots + a_K x_{t,K} = 0\,, \quad t = 1,2,\dots,T \qquad (11)$$

- **Homoskedasticity**

Conditional variance of error terms must be constant.

$$var\left(u_t \mid x_{t,2}, x_{t,3}, \dots, x_{t,K} \right) = \sigma^2, t = 1,2,\dots,T \qquad (12)$$

- **No Serial Correlation**

The disturbance terms must be uncorrelated conditional on current x.

$$cov\left(u_t, u_{t-s} \mid x_{t,2}, x_{t,3}, \dots, x_{t,K} \right) = 0, \quad s = 1,2,\dots,T-1 \qquad (13)$$

Some tests are applied to check the validity of estimators of heteroscedasticity, serial correlation, and cointegration under the assumptions mentioned above.

Augmented Dickey-Fuller Test

First, all variables are tested whether they are stationary; hence they can be used for the regression analysis. Augmented Dickey-Fuller test is to identify stationarity. If the series are non-stationary, this creates a spurious regression means inaccurate results and predictions. The method adds lagged differences to the three basic regression models. The model used is shown as:

$$\Delta y_t = \alpha + \gamma y_{t-1} + \lambda_t + v_t \qquad (14)$$

When the first difference is taken, variables become integrated of order zero, I(0) means series are transformed to stationary.

All variables are tested whether they are stationary. The first differences are taken in the Data Transformation part. Any seasonality is detected in the variables.

Breusch-Godfrey Test

A general test for autocorrelation in the errors that are residuals may be correlated over more than one period is applied. In the presence of serial correlation, inaccurate results are drawn from other tests and the knowledge of one deviation should not help to predict another. This test is useful because it generalizes to any order autocorrelation, robust to the inclusion of lagged dependent variables and valid asymptotically. There is also Durbin Watson test for serial correlation. But it is a restricted test to detect first order autoregression and inconclusive for first-order correlation. The model used is as follows:

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \rho_3 u_{t-3} + \cdots + \rho_q u_{t-q} + e_t \quad (15)$$

Finally, serial correlation is attempted to solve by taking first differences. However, the issue still remains which is an expected case in these types of series. Then the lagged form of the dependent variable is added as an independent variable to remove the serial correlation. The null hypothesis is rejected after this step. The model can be seen in the equation below.

$$\begin{aligned} r_t = \beta_0 &+ \beta_1 r_{t-1} + \beta_2 \Delta lnAddresses_t + \beta_3 \Delta lnTradVol_t + \beta_4 \Delta lnTransVol_t \\ &+ \beta_5 \Delta lnGold_t + \beta_6 \Delta lnCNY_t + \beta_7 \Delta lnEUR_t + \beta_8 \Delta lnGPB_t + \beta_9 \Delta lnSP500_t \\ &+ \beta_{10} \Delta lnCAC40_t + \beta_{11} \Delta lnDAX_t + \beta_{12} \Delta lnFTSE100_t + \beta_{13} \Delta lnSSE_t \\ &+ \beta_{14} \Delta lnCRX100_t + \varepsilon_t \quad (16) \end{aligned}$$

Breusch-Pagan Test

Time series models are estimated by OLS method assume homoskedastic disturbance means whether residuals have a constant and finite variance for any explanatory variable at the same time. Breusch Pagan test is one of the most common tests to check heteroscedasticity if $E(u_i^2) \neq \sigma^2$. In this case, the OLS estimators are not biased but inefficient. Thus, predictions of regression are inaccurate due to the inconsistency of the covariance matrix of the estimated coefficients. Hence, t-test and F-test are no longer valid. In the previous sections, this issue is solved by taking the natural logarithm of all variables and using robust standard errors.

Multicollinearity

When the explanatory variables are highly inter-correlated such as the variables in this study, the method used is susceptible to multicollinearity. To diagnose the multicollinearity, variance inflation factors for the explanatory variables (VIF) is used. The VIF is calculated for each explanatory variable by regressing a variable linearly on all the other variables. It measures how much variance of the estimated coefficients are inflated due to linear dependence with the independent variables. Since multicollinearity between macroeconomic variables is an expected situation due to high integration of financial markets and macroeconomic variables of a country, this issue can be ignored in such studies. It does not cause a problem unless analyzing the individual macroeconomic factors. Macroeconomic variables of this study cover a broad macroeconomic analysis; thus, it does not create a problem. Multicollinearity is only detected in CAC40 in stationary data. The degree of it is not high that is just above 8; hence it can be ignored. It is attributable to the highly engaged property of financial markets and macroeconomic variables. When non-stationary data is run, all explanatory variables show extremely high multicollinearity indicates that the spurious time series. The outputs of multicollinearity tests can be found in the Appendix in Table 1(A) and Table 1(B).

Generalized Autoregressive Conditionally Heteroskedastic Models for Time Series Analysis – GARCH (p,q)

In this section, ARCH and GARCH models are studied since they are essential tools in the analysis of time series data. Cermak's (2017) study is taken as a model but with differences. The unmodified model is used considering Bitcoin's nature while Cermak (2017) uses the modified model. The goal of ARCH/GARCH models is to provide a volatility measure used in the risk analysis. When the change in variance is correlated over time, then ARCH and GARCH methods can be used to model. In time series where the variation is increasing in a systematic way, called trend, this is attributed to dynamic forms of heteroscedasticity in series. Because evidence of heteroscedasticity is detected in this research's dataset, it is convenient to continue to study with dynamic forms of heteroscedasticity deal with the volatility. This conditional heteroscedasticity that evidenced leads to the first conditional model, known as ARCH. As a concise definition of ARCH models are mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances. For such processes, the recent history gives information about the one-period forecast variance (Engle, R.F, 1982).

Then, ARCH implies to GARCH model. After discussing conditional heteroscedasticity and ARCH, then GARCH is applied to series that exhibits volatility clustering. As started with the conditional heteroscedasticity, it occurs because the Bitcoin returns are volatile. Because there is a random variable, there is heteroskedasticity. This causes serial correlation that is an increase in variance also leads to an increase in the subsequent period means that series are conditional heteroskedastic also called as trending effects. These effects indicate serial correlation shows that an increase in variance conditionally on periods. In order to detect this conditional heteroskedasticity in series, ARCH/GARCH models are used.

Incorporation of conditional heteroskedasticity into the model introduces the ARCH model. The concept of the ARCH model is to allow more accurate volatility estimation in case of current volatility is conditional on the previous period's observation if information of the previous period is considered (Cermak, 2017). Because OLS cannot be used when the variance of residuals fluctuates in case of Bitcoin price, ARCH should be required to transform OLS residuals into weighted least squares (WLS). It is important to mention that ARCH can be applied to series have any trends or seasonality means have no serial correlation. ARCH model for the variance of model y_t is described as the following equation:

$$var(y_t \mid y_{t-1}) = \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \qquad (17)$$

where,

σ_t^2 = conditional variance at time t

u_{t-1}^2 = ARCH term squared residual return from previous time

In order to avoid negative variance and ensure for stationary, $\alpha_0 \geq 0$, $\alpha_1 \geq 0$ and $\alpha_1 < 1$ should be practiced.
ARCH(q) stands for the number of lags of the squared residual return from previous periods which represents that the conditional variance. ARCH(1) is the first order model. The equation for ARCH(p) is described as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_p u_{t-q}^2 \qquad (18)$$

One step further, Bollerslev (1986) proposed an extensive model of ARCH called GARCH which points out the insufficiency of ARCH in case of the high order. The model displays the volatility clustering in the time-varying. Since the ARCH model is somewhat restrictive, the constraint becomes complicated when orders are high, and conclude with the inaccurate forecasts. The large residual means a crisis does not have the same persistence as an actual crisis that observed (Cermak, 2017). Therefore, GARCH(p,q) model extended of ARCH(q) with autoregressive terms of the volatility is applied to capture a shock that is large residuals. To investigate the factors, affect the variance of Bitcoin prices, it is crucial to model the variance of residuals. The model introduces a new parameter for the lag variance terms.

- p: the number of lag variances
- q: the number of lag residual errors introduced with the GARCH model

General GARCH(p,q) equation can be seen as follows:

$$X_t = \sigma_t \varepsilon_t \qquad \varepsilon_t \sim IDD(0,1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 X_{t-1}^2 + \cdots + \alpha_p X_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \qquad (19)$$

To hold stationary condition; $\alpha_j \geq 0,\ \alpha_p > 0,\ \beta_j \geq 0,\ \beta_q > 0$ and $|\theta| < 1$

The common practice is to use the symmetric GARCH(1,1), first order in the model, which is also applied in this study. Symmetric GARCH equation is described in the following equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (20)$$

To hold stationary condition, $\alpha_0 \geq 0,\ \alpha_1 > 0, \beta_1 \geq 0$ and $|\alpha_1 + \beta_1| < 1$
where,
σ_t^2 = conditional variance at current period t
α_0 = estimated the weighted average of the long run average variance
ε_{t-1}^2 = ARCH term; squared residual return from the previous period
σ_{t-1}^2 = GARCH term; variance from the previous period

An ARCH and a GARCH term are included in the regression for this study. The benefit of using a GARCH model is that the variance may have a long memory with low p and q means that also ARCH(∞). $\alpha_1$is the ARCH component that estimated the relation to the conditional volatility observed in the previous period means that specifying the degree of volatility of the variance process. β_1 is the GARCH component that the estimated forecasted variance from last period. According to GARCH(1,1) model, "$\alpha_1 + \beta_1$" represents of persistence which means the rapidity of tailing off large volatility following a shock.

To fulfill the requirements of running GARCH(1,1) model, two critical conditions are actualized to apply the model. The conditions to be tested are whether the residual is conditional heteroskedastic and autoregressive conditional heteroscedasticity, whether there is ARCH effect in the residual.

The first condition, there is evidence of the GARCH model because the variance at a period has a positive relationship with variance at the previous period. This implies that periods of high volatility tend to follow high volatility at the next periods or low variability periods tend to follow low variability periods. Hence, the large returns in Bitcoin lead to large returns and small returns lead to small returns in the subsequent period. In this case, conditional heteroscedasticity functions as a leading indicator because the time series appears as a cluster of high or low volatility. Statistically, the conditional variance from the previous period is not constant over time indicated that conditionally heteroscedasticity. Concisely, the variation in volatility which is a demonstrative stylized fact of Bitcoin price make this study to use GARCH model appropriate. The results of the clustering volatility test are displayed in Figure 12. To plot the graph, firstly ARMA model which is ARIMA(1,0,1) is performed on log returns. Then, residuals are predicted of the ARMA model.

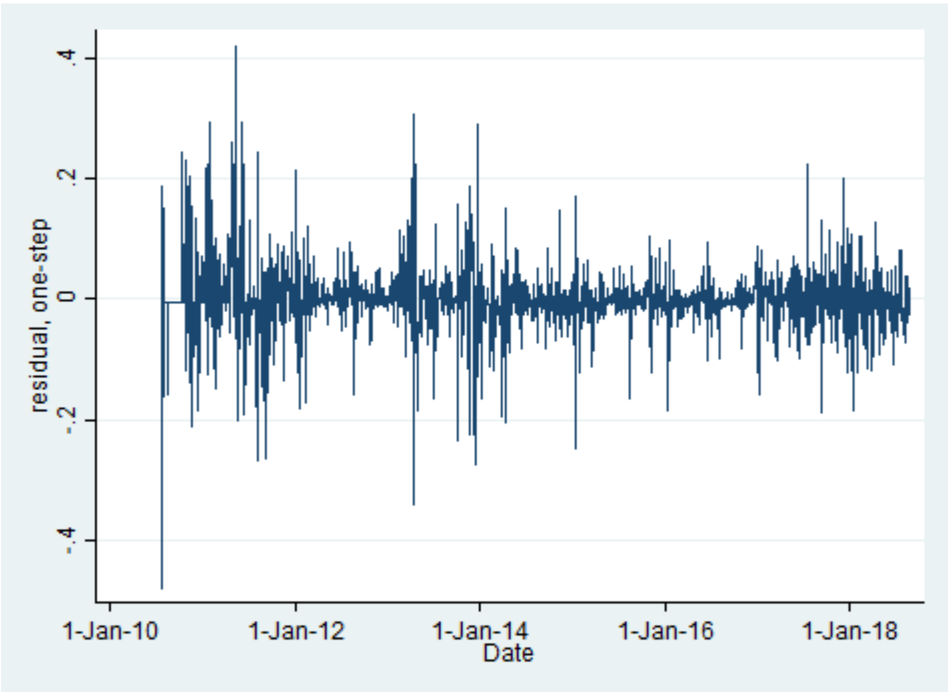


Figure 12: Test for volatility clustering in the residuals

In order to check the second condition, ARCH-LM test is applied to find out whether there is a serial correlation of the heteroskedasticity. This test is the standard approach to detect autoregressive conditional heteroscedasticity. The determination of ARCH effect is commonly followed by modeling time-varying heteroscedasticity which is GARCH(1,1) model. To express that if GARCH is stationary, Lagrange Multiplier (LM) test to assess the significance of ARCH effects is specified. The detection of strong ARCH effect in the residuals of first differenced log prices of Bitcoin by LM test makes performing GARCH model appropriate. To run ARCH-LM test, a large number of lags are used, and strong evidence of ARCH effect in the mean equation is detected. The results of the ARCH-LM test can be seen in Table 11.

Table 11

LM Test for Autoregressive Conditional Heteroskedasticity (ARCH)

Lags(p)	chi2	df	Prob > chi2
1	138.036	1	0.0000
2	161.394	2	0.0000
3	213.630	3	0.0000
4	209.118	4	0.0000
5	226.033	5	0.0000
6	235.582	6	0.0000
7	236.104	7	0.0000
8	236.403	8	0.0000
9	234.800	9	0.0000
10	238.705	10	0.0000
11	240.257	11	0.0000
12	241.981	12	0.0000

H0: no arch effects vs. H1: ARCH(p) disturbance

To introduce the GARCH(1,1) model, two conditional equation is used as a mean and variance equation. As the first step, the mean equation is estimated because the variance is a function of the mean. Thus, the mean equation is needed to formulate the GARCH model. This equation is the part of the forecast by using the lags. If the time series is stationary, AR, ARMA or MA to model returns by building the mean equation. The equation can be seen as follows:

$$r_t = \beta_0 + \beta_1 r_t + \cdots + \beta_K r_{Kt} + \varepsilon_t \qquad \varepsilon_t \sim IDD(0,1), \ |\theta| < 1 \qquad (21)$$

AR(1) model is used in the mean-variance equation since it is the most practiced model in volatility of returns. The equation can be interpreted as returns of this time t are forecasted based on the previous period, $t - 1$.

The variance equations is as following:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (22)$$

where,
ε_{t-1}^2 = ARCH term; squared residual
α_1 = ARCH component
σ_{t-1}^2 = GARCH term; variance
β_1 = GARCH component

The variance equation is the primary interest of this analysis rather than mean equation (21) direct to the variance equation (22). The squared residual serves as the ARCH term. The term represents that how the variance of Bitcoin price is affected on the period t from the previous variance on the period $t-1$. GARCH term derived from mean equation 20 refers that whether the variance in Bitcoin price at time t has a correlation with variance of the price at time $t-1$.

There are two ways of conducting the GARCH(1,1) model by including exogenous explanatory variable and not including. If the explanatory variable is added, both AR(1) and GARCH(1,1) models are required to modified meaning that the mean and variance equations are needed to alter. The modified AR(1) and GARCH(1,1) models are applied in the academic researches. For example, Baur et al. (2018) and Dyhrberg (2016) performed the modified equations with exogenous explanatory variables. In general, it is a common practice in financial time series. However, Bitcoin has any internal variables as may be included as an exogenous explanatory variable. According to Cermak (2017), Bitcoin does not have internal variables except a few of them; they cannot be used as a function of returns due to it has no intrinsic value. The market forces its only drive its value. Therefore, this study takes into account the properties of Bitcoin and does not include exogenous explanatory variable. If the exogenous explanatory variable is added, the models can be found in the Appendix in equation 1(A) and 1(B). The results of the unmodified GARCH(1,1) model can be seen in Table 12 to detect a potential relationship between the volatility of Bitcoin and explanatory variables.

Table 12

ARCH Family Regression

	Coefficients	Standard Errors
Return		
Unique Address	-0.155*	0.007
Trade Volume	0.006***	0.001
Transaction Volume	0.006	0.008
Gold	0.189*	0.082
CNY/USD	2.026***	0.360
EUR/USD	-0.179	0.213
GPB/USD	0.036	0.235
S&P500	-0.237*	0.109
CAC40	-0.080	0.215
DAX	0.128	0.201
FTSE100	-0.027	0.192
SSE	0.084	0.043
CRX100	0.220***	0.002
Constant	0.001	0.001
Arch L1	.364***	.033
Arch L1	.710***	.017
Constant of ARCH/GARCH	0	0
N observations	1,391	
Wald χ^2	12960.64***	

Note: *p<.05, **p<.01, ***p<.001

Results

ARCH(α) and GARCH(β) terms are statistically significant in the variance equation. The ARCH term means that the return from previous period influences the volatility of Bitcoin during the current period. The GARCH term concludes that the volatility of Bitcoin in the current period is affected by the volatility of the previous period indicates that persistence. Since GARCH term is larger than ARCH term (β > α), volatility of prior period should be predicated on Bitcoin volatility forecasting for the future. Because the volatility effect of previous period dominates the past shock effects. Also, chi(2) value which is very high shows that the model is significant.

As explanatory variables, Unique Address, Trade Volume, Gold, CNY/USD, S&P500 and CRX100 are significant to forecast Bitcoin's future volatility. As Bitcoin grows, macroeconomic and financial variables reflect it.

One most remarkable exploration of this analysis is that the Chinese Yuan reaction which is significant at the highest level. However, this is an expected outcome since China is the most Bitcoin traded country among all. According to Deutsche Bank's report (2017), while Yuan was composing less than a 10% of the Bitcoin trading in 2012, that percentage became almost 100% in 2017. As observed in the results, Bitcoin's volatility is affected by the return in the exchange rate of CNY. One potential explanation is that if Yuan goes up compared to US dollars, Bitcoin becomes cheaper for people who use CNY. As a result, more Bitcoin can be bought at the same price in dollars. In another way, more people can afford to buy it. The volatility of the Yuan can predict the volatility of Bitcoin at the next period. The volatility shocks that affect the CNY rate influence the Bitcoin price.

The second significant outcome is that the return of Gold at a previous period is useful to forecast the volatility of Bitcoin in the subsequent period. But this relationship is not at a strong level. The volatility of Bitcoin is not very sensitive to price changes in Gold relative to the Yuan. Because they both have common properties as an asset, the direction of a volatility shock would affect their price changes similarly.

The third finding is that there is a negative correlation between S&P500 and Bitcoin. A positive volatility shock in S&P500 at previous period leads to decrease the volatility of Bitcoin at the following period. This movement may be inferred as investors treat Bitcoin as a safe-haven asset in the US. When the risk of the US stock exchange increase, the volatility of Bitcoin reduces because investors convert their holdings to Bitcoin from stocks. In other words, when uncertainty arises in the US stock market, investors tend to buy Bitcoin which has a negative correlation with the equities. There are two possible events to support that how external shocks affect Bitcoin's volatility. First, Trump's shocking victory for the presidency of the US. It caused considerable uncertainty in business and political areas for the future. Hence, the stock market was reflected with an immediate drop. The price drop in stock markets caused a surge in Bitcoin prices because people who had doubts run to an alternative asset such as gold and Bitcoin recently. In the previous part, the model included event dummy variables supports this outcome. The second potential example of this negative relationship is the rejection of Bitcoin ETFs proposal by the SEC in 2017 after that Bitcoin price plummeted.

Another finding is that positive volatility shock in CRX100 at the past period implies to increase in volatility of Bitcoin at the next period which is an expected outcome. Because almost all other cryptocurrencies move together Bitcoin in the same direction. Besides, Bitcoin covers nearly half of the market. It has a major portion among currencies.

Last findings come from technical aspects that are Unique Address and Trade Volume. Increase in trading volume changes at the past period can affect the volatility of Bitcoin in the future. When the volume goes up and down so frequently at the prior period, the return of Bitcoin also fluctuates at the next period more. On the other hand, an upward volatility shock in the unique address at the previous period leads to a decline in the volatility of Bitcoin in the following period. The possible explanation is that the more unique addresses mean more users may make Bitcoin more stable in the future. When the adoption rate of Bitcoin increases, it becomes a less risky asset. Figure 13 represents the conditional variance of the daily Bitcoin returns implies that there is a decrease in variation over time. The figure below supports the last findings in this research.

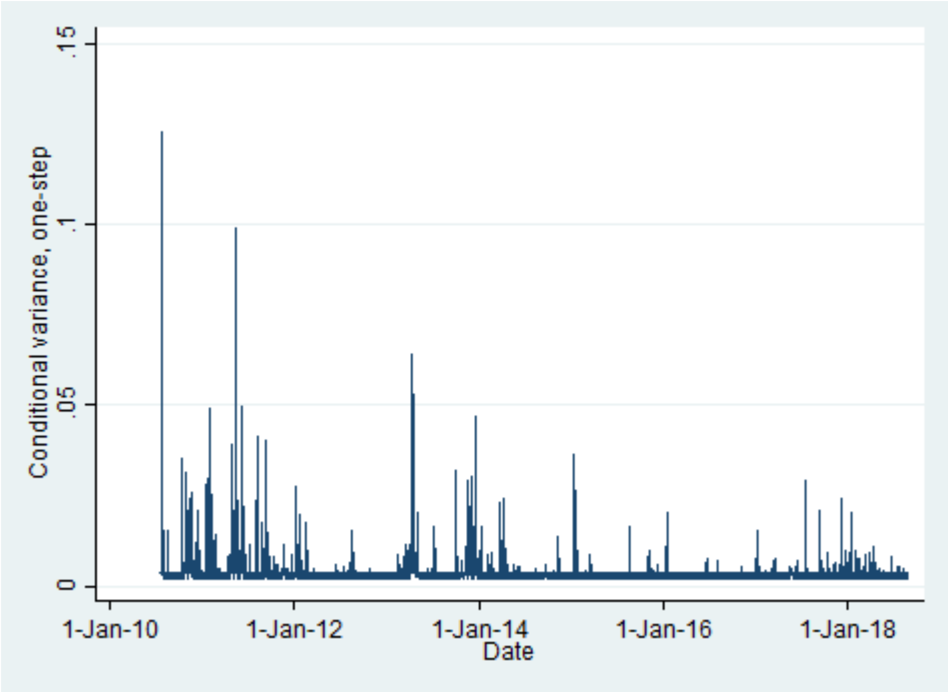


Figure 13: Conditional variance of daily Bitcoin returns

Concluding Remarks

Although the price of Bitcoin has been becoming more stable and the adoption rate increasing, it is still very volatile relative to fiat currency. Its fluctuation can be vast and dramatic due to external events; it is far from being a safe investment currently. However, a downward trend is evidenced over time. Investors mainly use bitcoin as an investment tool and a hedge against stock markets volatility. The variation of the Bitcoin is sensitive to shocks in China mostly, meaning that changes in Yuan rate dominate the volatility of Bitcoin at the next period. Investors willing to invest in Bitcoin should watch Chinese Yuan rate against the US dollar to get insight into the Bitcoin volatility in the future. Secondly, uncertainty in US stock market influences the instability of it but not too strong. The negative relationship shows that investors convert their investments from stock markets to the Bitcoin market during uncertain periods in the stock markets. On the other hand, no evidence is found that it is the case in European markets.

The final point to highlight is that the lack of centralization in Bitcoin. While investors minimize the idiosyncratic risk by diversifying their portfolios, central banks reduce the systematic risk that is undiversifiable in the financial markets. The nature of Bitcoin does not allow the minimizing risk since it has no centralization system. Thus, investors should be careful investing in it even though the volatility decreases by the time.

One of the limitations of the study is the scope. It investigates only one cryptocurrency. The literature still lacks in other cryptocurrencies such as Ethereum. The interest in Ethereum has exceeded Bitcoin in South Korea. Future research could be extended to other digital currencies. Another limitation of the study is limited in three exchange rates. Further study might apply more extensive empirical model on the different exchange rates.

Appendix

Table 1(A)

Variance Inflation Factors for the Stationary Explanatory Variables

	VIF
CAC40	9.79
DAX	7.23
FTSE 100	4.04
EUR	1.90
GPB	1.78
S&P500	1.48
Gold	1.24
Unique Addresses	1.11
Trade Volume	1.11
CNY	1.07
Transaction Volume	1.06
SSE	1.05
CRX100	1.02
Mean VIF	2.61

Table 1(B)

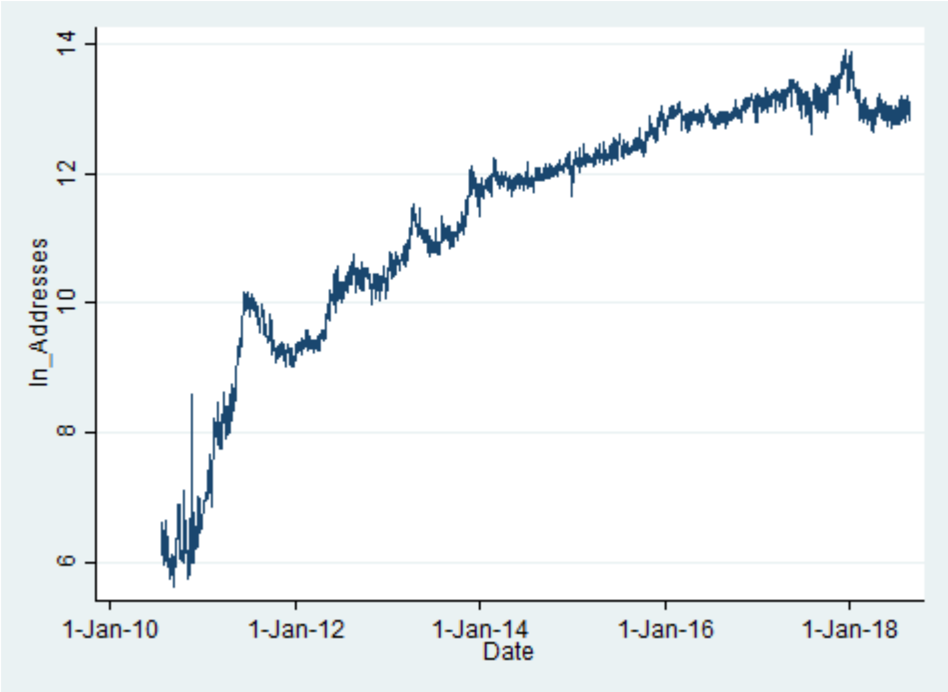
Variance Inflation Factors for the Non-Stationary Explanatory Variables

	VIF
DAX	73.60
CAC40	38.59
Transaction Volume	37.04
Unique Addresses	34.32
GPB	25.13
EUR	24.88
CRX100	19.92
S&P500	17.61
FTSE100	15.69
CNY	13.72
SSE	10.29
Trade Volume	8.41
Gold	2.95
Mean VIF	24.78

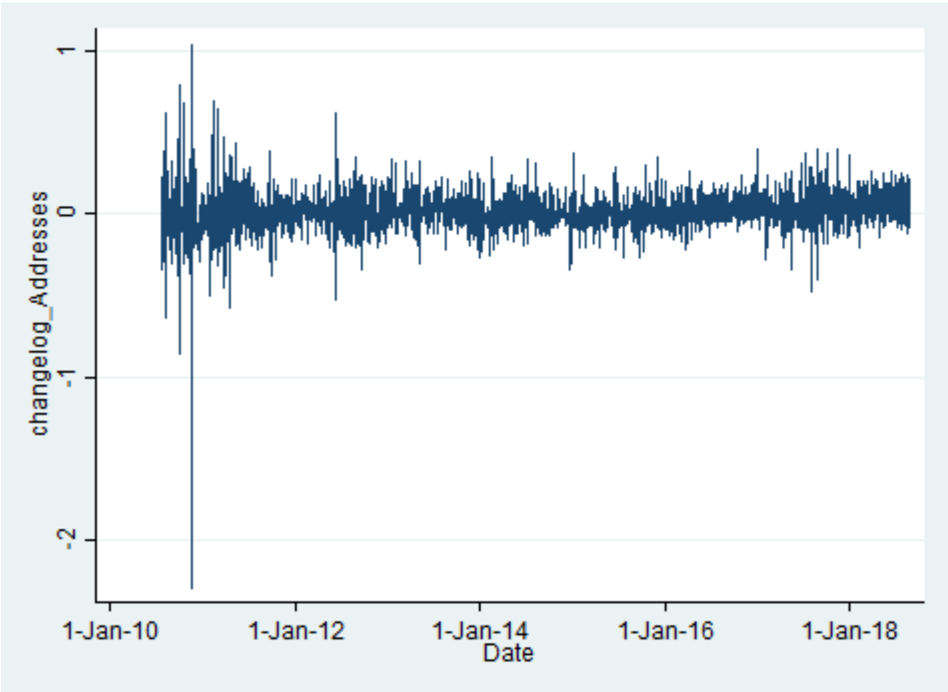
Figures 2(A)

Unique Addresses Transformation

(a)

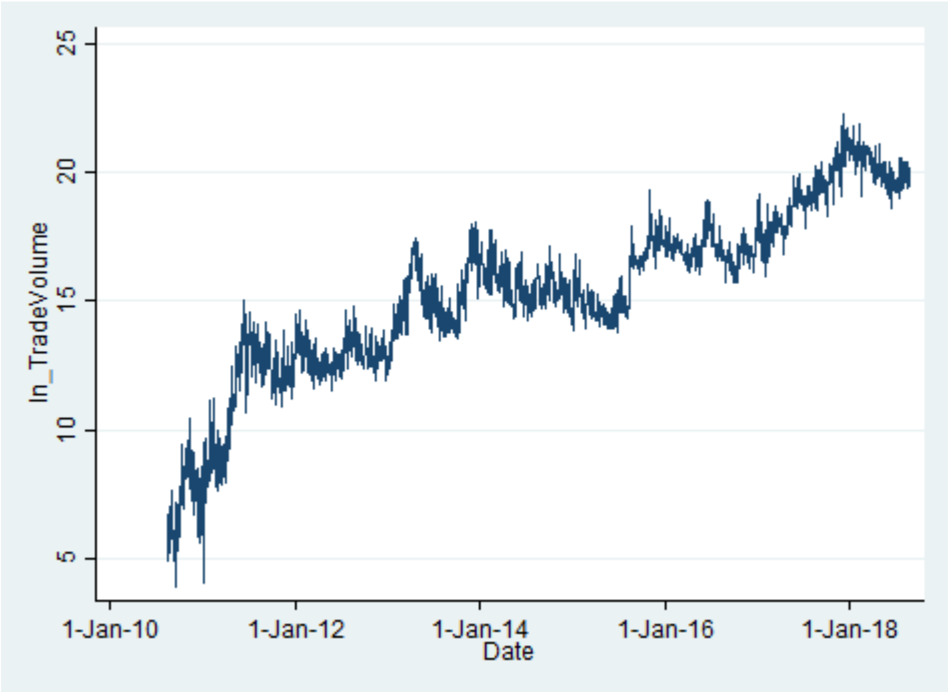


(b)

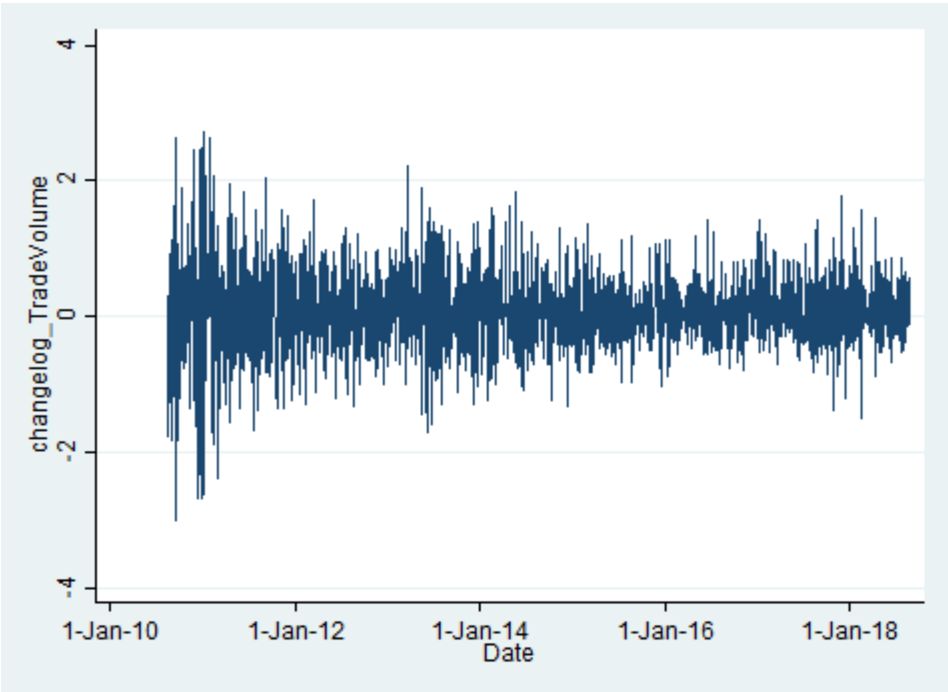


Trade Volume Transformation

(a)

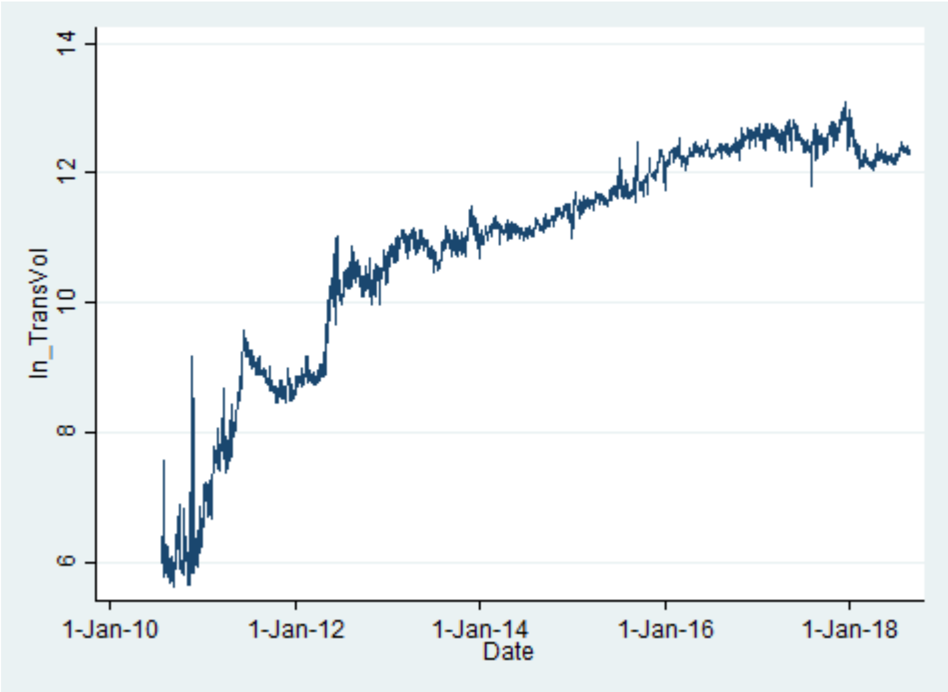


(b)

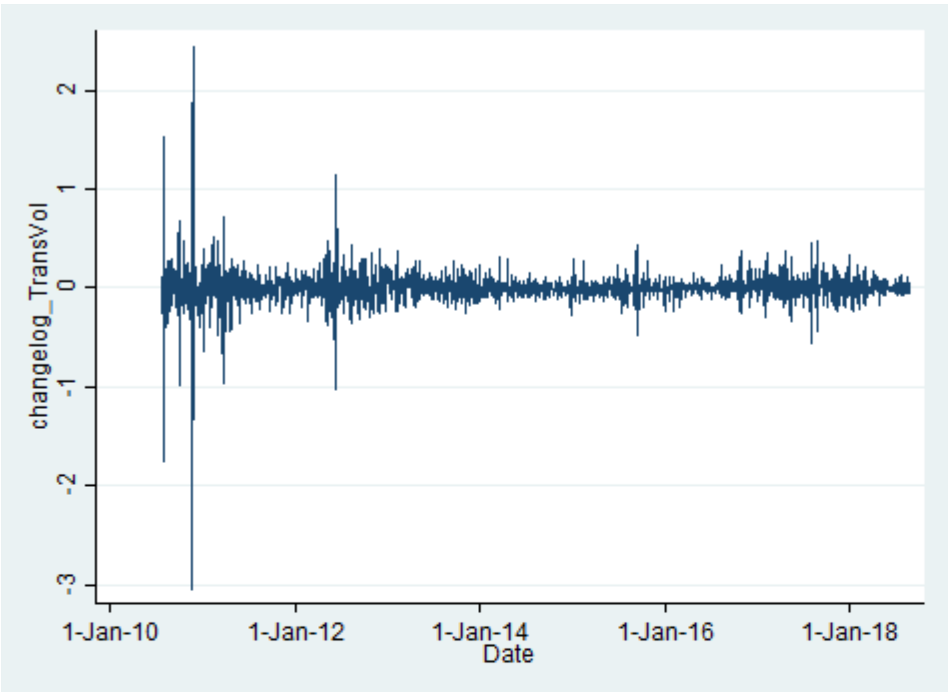


Transaction Volume Transformation

(a)



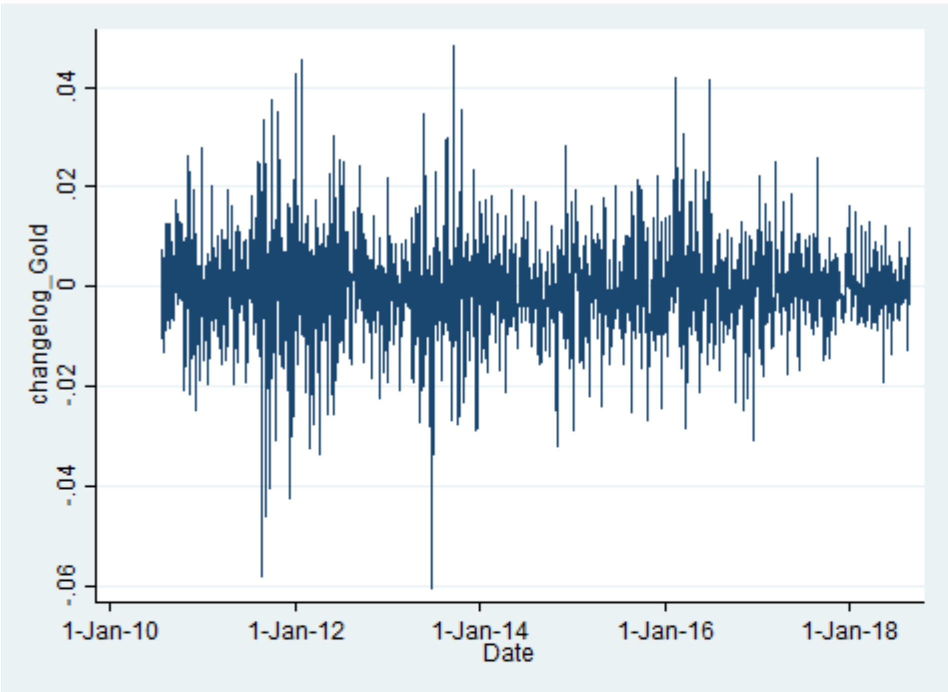
(b)



Gold Transformation

(a)

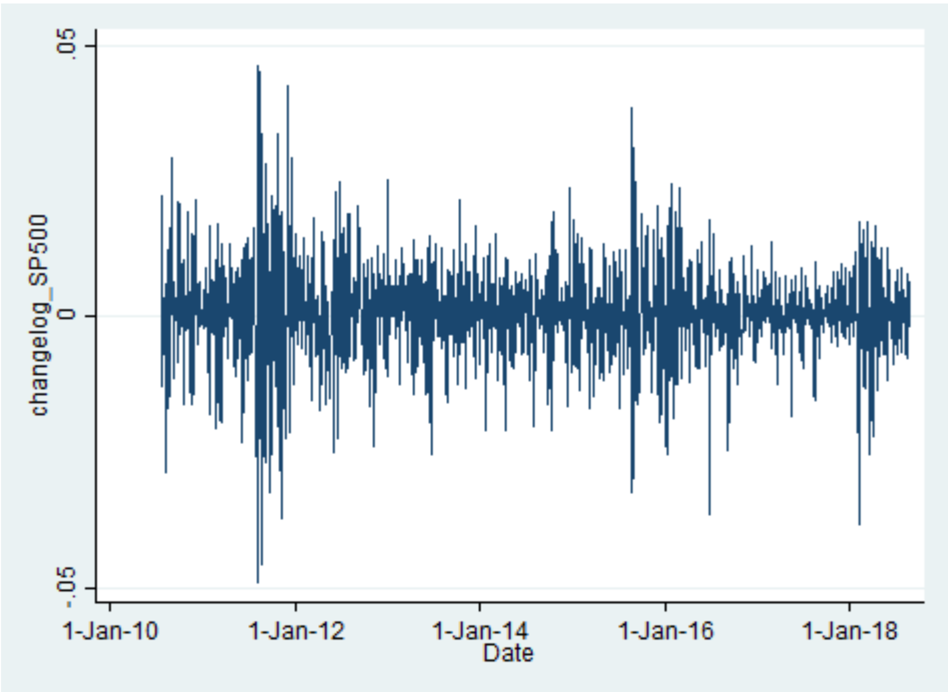
(b)



S&P500 Transformation

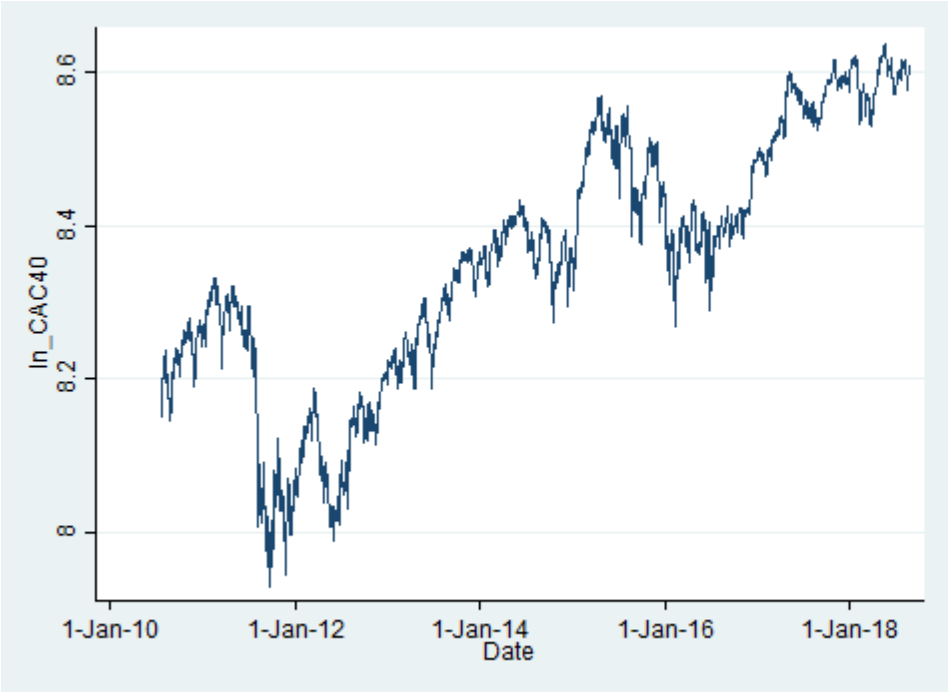
(a)

(b)

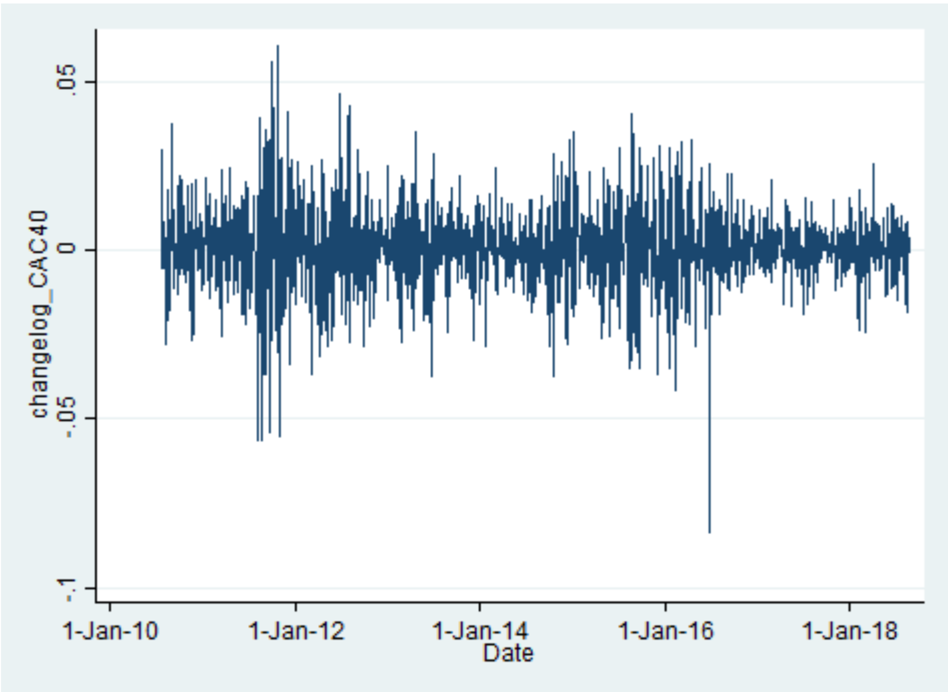


CAC40 Transformation

(a)

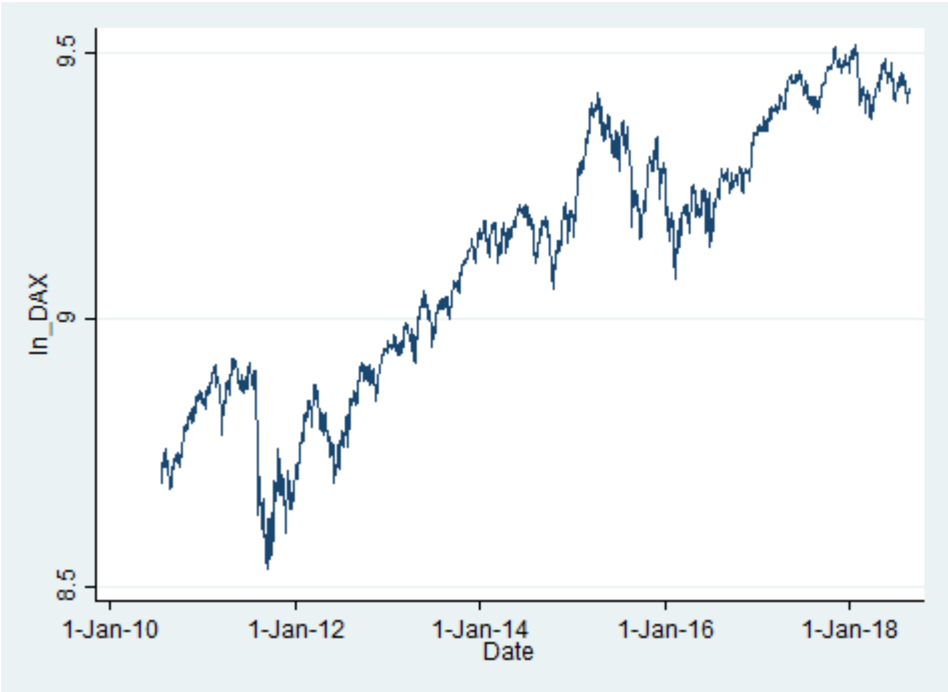


(b)



DAX Transformation

(a)



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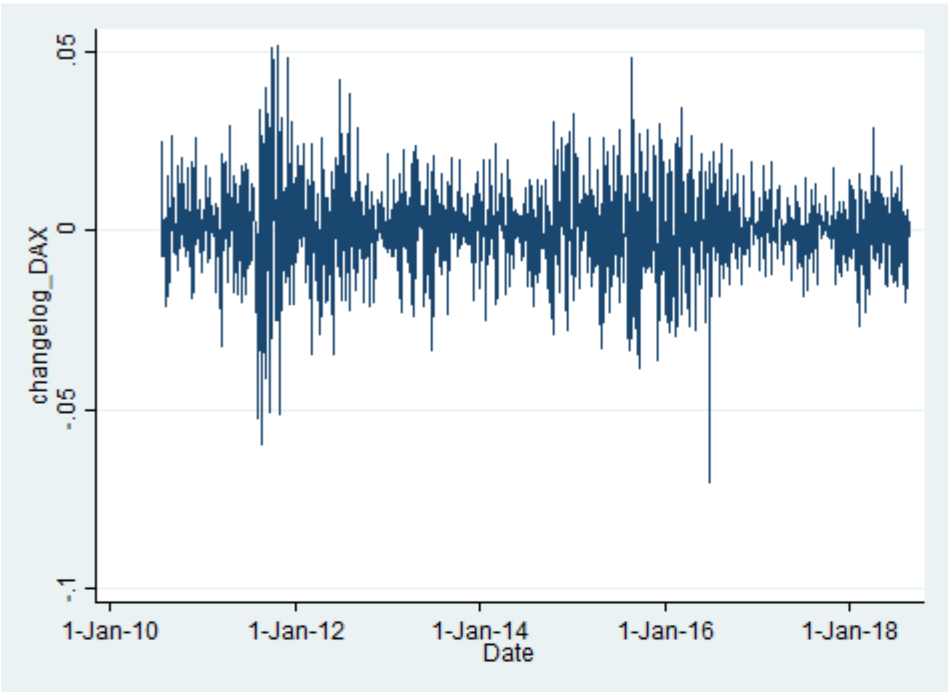
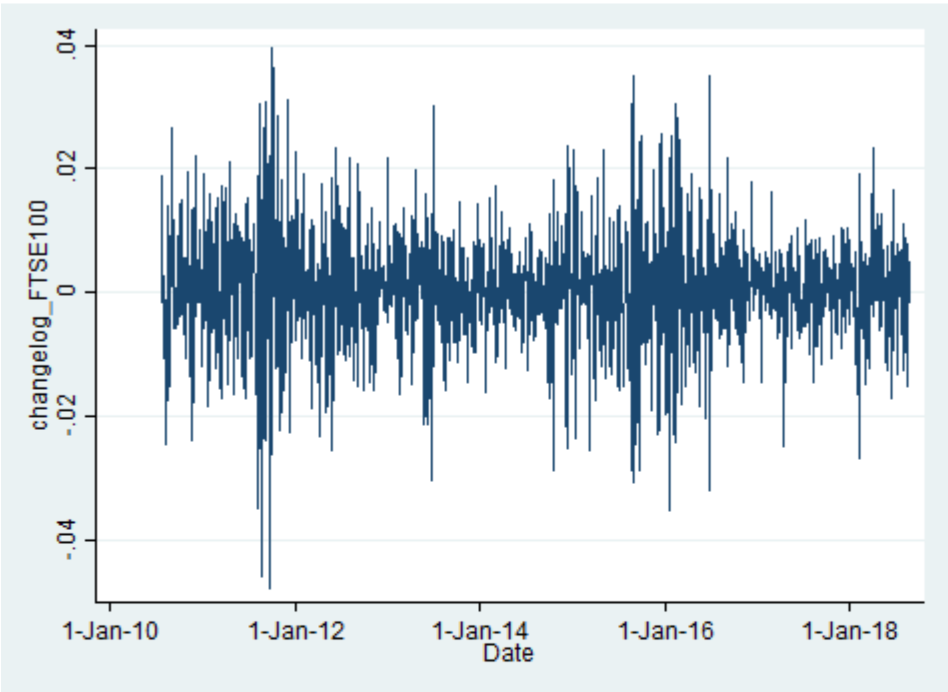


FTSE100 Transformation

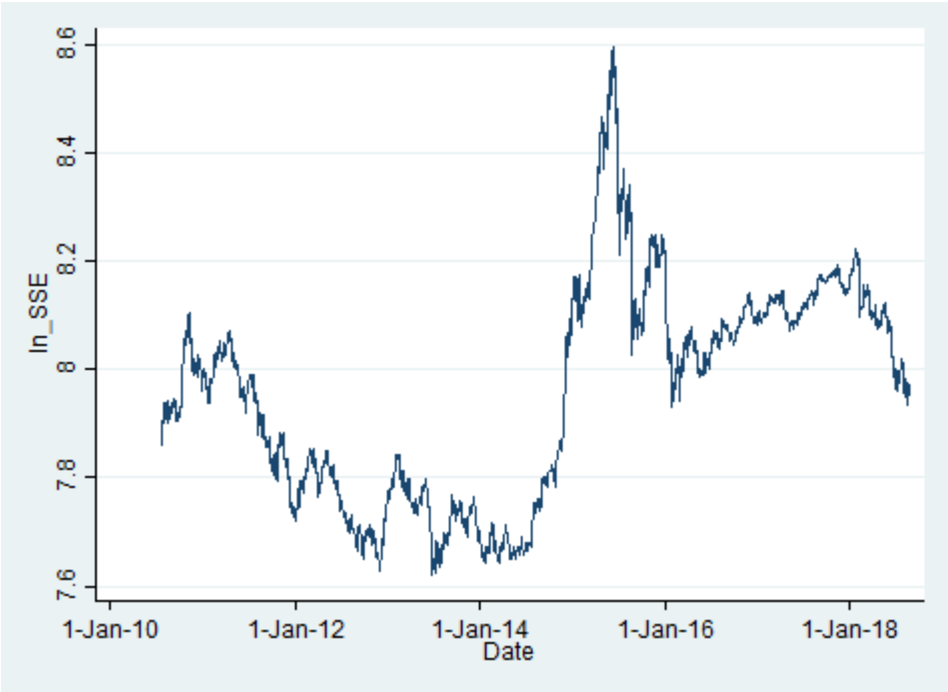
(a)

(b)

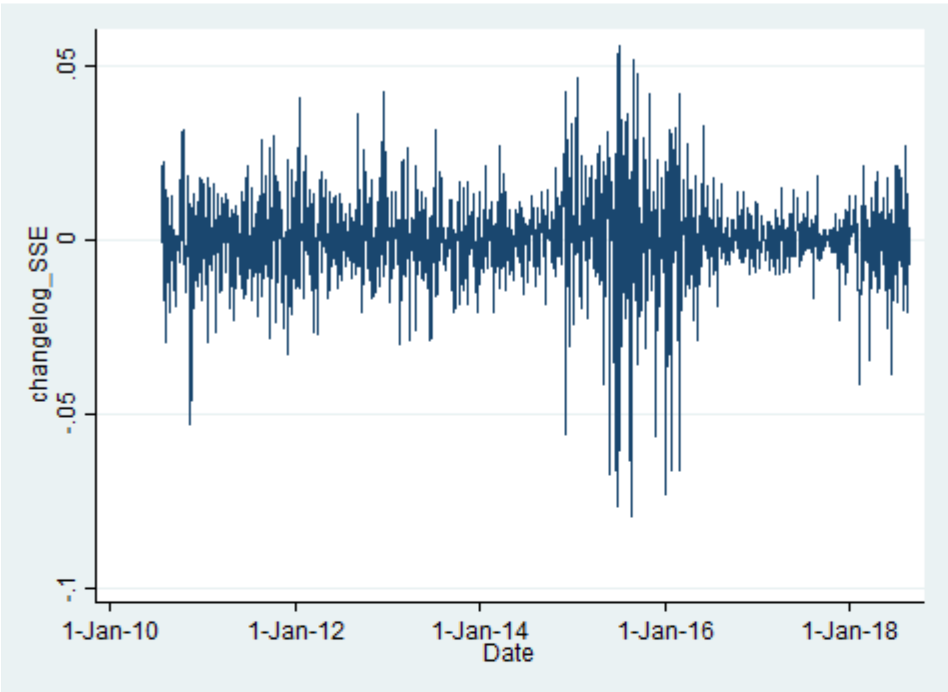


SSE Transformation

(a)



(b)



Currency List of the CRX100 Index

Bitcoin	Zcash	Verge	RChain	MCO
Ethereum	OmiseGO	Pundi X	MOAC	Aurora
XRP	Lisk	Augur	Chainlink	GXChain
Bitcoin Cash	Bytecoin	Bytom	Dentacoin	Nxt
EOS	Ontology	Holo	Aelf	Nebulas
Stellar	Bitcoin Gold	Electroneum	TrueUSD	Elastos
Litecoin	Qtum	Metaverse ETP	Dropil	Bitcoin Private
Tether	Bitcoin Diamond	Basic Attention Token	Hshare	MonaCoin
Cardano	0x	Stratis	Aion	Gas
Monero	Decred	Waltonchain	Huobi Token	ZCoin
Dash	Zilliqa	Cryptonex	DigixDAO	Theta Token
IOTA	Nano	Golem	QASH	CyberMiles
TRON	BitShares	Status	BitcoinDark	WAX
NEO	DigiByte	Komodo	Mixin	Dragonchain
Ethereum Classic	Maker	ReddCoin	Horizon	Odyssey
Binance Coin	ICON	Mithril	Bancor	Power Ledger
NEM	Waves	KuCoin Shares	Decentraland	Kyber Network
VeChain	Aeternity	Wanchain	Ark	PIVX
Tezos	Steem	IOST	FunFair	Nexus
Dogecoin	Siacoin	Ardor	TenX	Eternal Token

Market Cap of 100 Cryptocurrency

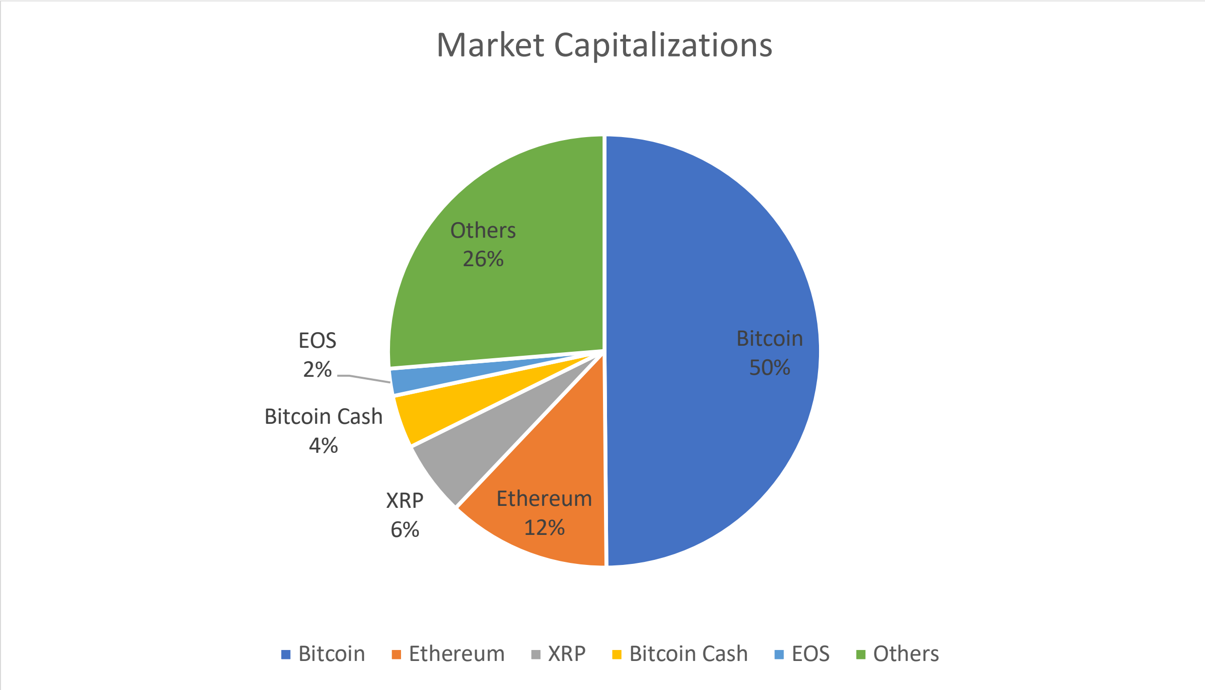


Chart 1(A): The 5 largest and other cryptocurrencies distributions

Trading Volume of CRX100

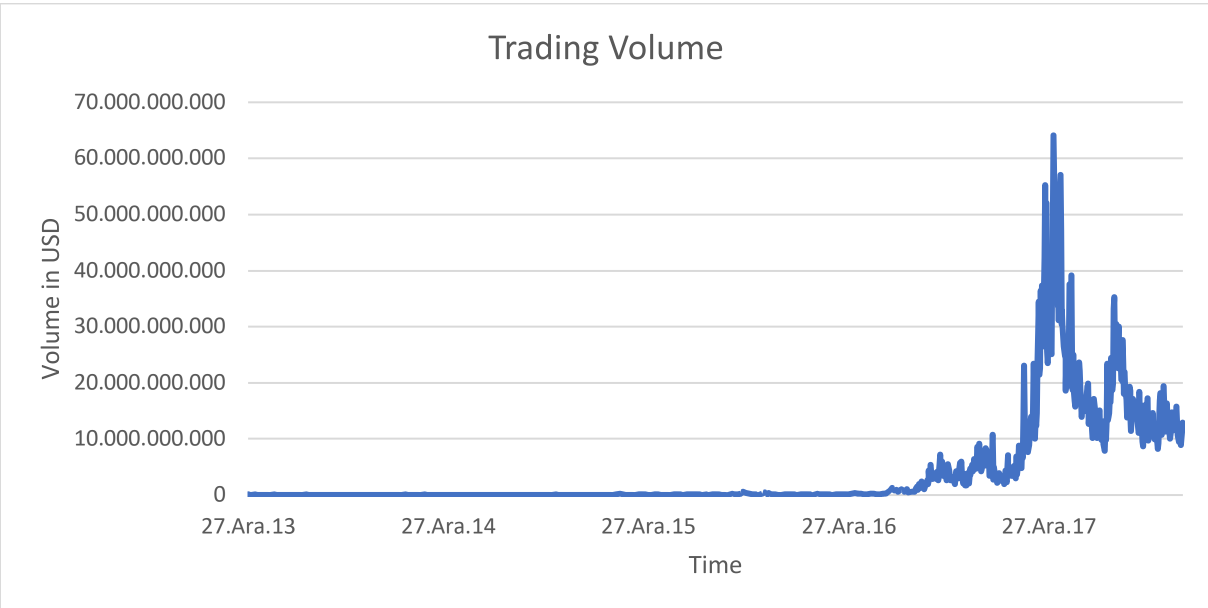


Chart 2(A): Trading Volume of the top 100 currencies over time

The Modified Equations included Exogenous Explanatory Variables

The modified mean equation;

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 \Delta lnAddresses_{t-1} + \beta_3 \Delta lnTradVol_{t-1} + \beta_4 \Delta lnTransVol_{t-1} + \beta_5 \Delta lnGold_{t-1} + \beta_6 \Delta lnCNY_{t-1} + \beta_7 \Delta lnEUR_{t-1} + \beta_8 \Delta lnGPB_{t-1} + \beta_9 \Delta lnSP500_{t-1} + \beta_{10} \Delta lnCAC40_{t-1} + \beta_{11} \Delta lnDAX_{t-1} + \beta_{12} \Delta lnFTSE100_{t-1} + \beta_{13} \Delta lnSSE_{t-1} + \beta_{14} \Delta lnCRX100_{t-1} + \varepsilon_t \qquad 1(A)$$

The modified variance equation;

$$\sigma_t^2 = \exp(\lambda_0 + \lambda_1 \Delta lnAddresses_{t-1} + \lambda_2 \Delta lnTradVol_{t-1} + \lambda_3 \Delta lnTransVol_{t-1} + \lambda_4 \Delta lnGold_{t-1} + \lambda_5 \Delta lnCNY_{t-1} + \lambda_6 \Delta lnEUR_{t-1} + \lambda_7 \Delta lnGPB_{t-1} + \lambda_8 \Delta lnSP500_{t-1} + \lambda_9 \Delta lnCAC40_{t-1} + \lambda_{10} \Delta lnDAX_{t-1} + \lambda_{11} \Delta lnFTSE100_{t-1} + \lambda_{12} \Delta lnSSE_{t-1} + \lambda_{13} \Delta lnCRX100_{t-1} + \varepsilon_t \qquad 1(B)$$

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