Network Effects in Cryptocurrency Market: Speculative Demand vs. Transactional Demand

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Abstract

We want to investigate more into how the cryptocurrency market is behaving, and Bitcoin will forever be the dominant player. Previous literature provided great insights on what driving the price of Bitcoin, but not so much on the market as a whole, so we want to fill in the gap by examining the relationship between major cryptocurrencies to better understand how different demands, namely transactional and speculative demand are impacting their relationships. Our preliminary results show that there are still evidence of Bitcoin's transactional and speculative demand, and Bitcoin's dominant player's role may be jeopardized in the decentralized payment system market. In addition, since late December 2017, speculation for Bitcoin has been decreasing for a number of reasons, but not concerns about cyber-attack is not likely to be one of them.

1. Introduction

Bitcoin was introduced in 2009, with the idea that transactions can be made anonymously and decentralized. Often time, Bitcoin and other digital currencies are compared to cash, since they share attributes like medium of exchange, store of value, … However, these digital currencies are purely digital, used primarily online and are extremely volatile (Figure 1 &2), which made many of their critics deny their ability to be a "currency".

The emerging market of cryptocurrencies is full of ambiguities, which motivates me into studying this subject, particularly, competition between different cryptocurrencies in this market. By understanding the competition between different cryptocurrencies and how they interact with one another in this market, WEhope to see if Bitcoin collapses, despite its recent rapid increase in price and demand, will other cryptocurrencies be able to replace it and maintain the market, or will the collapse of Bitcoin mark the end of this nascent market?

Network effects, the value of a product or service increases as the number of users increases, is one of the main characteristics of this market. According to Katz and Shapiro from the network effects literature [1], such environment is likely to create a winner-take-all dynamic, and only one dominant player remains in the market. One prime example of the network effect is the competition between Facebook and Google+. At the time, while Google+ was designed with much better functions compared to Facebook, it could not gain significant market share, and as a result, lose the "social media battle", because of the network effect created by Facebook users.

The currency market also exhibits this effect. The more popular a currency is, the more useful it becomes to own it, and as a result, its demand increases proportionally with its popularity. In terms of cryptocurrency, Bitcoin is the first ever cryptocurrency and the most well-known one in the market. However, it has many shortcomings[1], that were addressed and improved in the newer cryptocurrencies. Therefore, can Bitcoin's first-mover advantage create a network effect large enough for it to maintain its status as the dominant player in this market?

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[1] WEwill go in more details about Bitcoin's shortcomings in later section

Previous literature contradicted each other in whether Bitcoin will maintain its dominant role in this nascent market. Gandal et al. (Gandal and Halaburda, 2014) suggested that during the 2014 period, strong network effect favoring Bitcoin became more apparent as Bitcoin gains its popularity. However, El Bahrawy et al (2017) suggested that though Bitcoin's price is increasing at an exponential rate, this currency is actually losing ground to its alternatives.

In my study, we want to investigate more into how the cryptocurrency market is behaving. While the previous studies provide significant insights, we suspect that the uncertainty in the drivers of Bitcoin's demand is causing the mismatch in these researchers' findings, since both of the papers only take into account Bitcoin's price when they calculate the network effect rather. Therefore, we want to better understand the different forces that driving demand for Bitcoin, namely two main ones: transactional demand and speculative demand[2], and find out if the network effect exists at all.

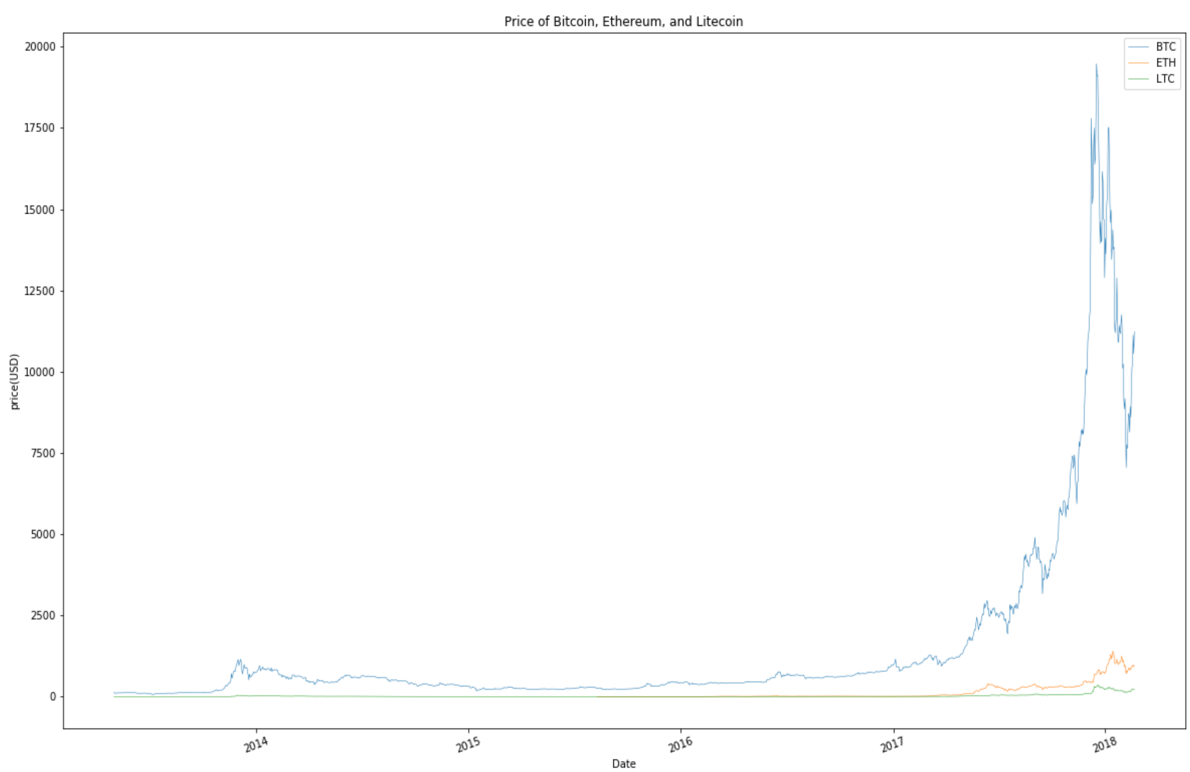

Figure 1: Price of Bitcoin (blue line), Ethereum (yellow line), and Litecoin (green line)

[2] Definition of these two terms will be explained in the Economics Model Section

Figure 2: Logged price of Bitcoin, Ethereum, and Litecoin

2. Literature Review

Brief Background on Cryptocurrencies and Blockchain

Bitcoin, the first cryptocurrency, was introduced in 2009, and followed by many cryptocurrencies. Cryptocurrencies have no central authorities over transactions, or in other words, decentralized. They use cryptography techniques for secure communication in the presence of third parties, control transactions, manage supply and detect fraud. Once confirmed, all transactions are stored digitally and recorded in a “block”.

When each block is closed, miners have the opportunity to solve a mathematical problem to provide the key to lock it. Whoever solves it first will get a reward of a certain amount of Bitcoin, which serves as an incentive for people to mine, maintain the secure system, and generate new coins. After each block is locked, it then gets placed in a chain of pre-existing blocks, which is why this system is called “blockchain”. As the blockchain continues to grow, the math problems get harder and the coin rewards get smaller.

The supply of most cryptocurrencies increases at a predetermined rate, and cannot be changed by any central authority. This creates concerns about the deflationary aspect of the currency due to its limited supply[3]. However, there is a constant debate among economists whether deflation is good for the economy. Keynesian economists argue that deflation is bad for the economy because it incentivizes individuals to save money instead of spending it. On the other hand, the Austrian economists claim that as deflation occurs, prices as well as the cost for production also decreases, but profits will not change. Therefore, it will increase incentive for entrepreneurs to invest in long-term projects.

Bitcoin's algorithm provides an effective safeguard against "counterfeit" by assuming that the majority of users are honest. If a record of someone is different than anyone else, it is likely that this person cheated, and their record will become invalidated. So far, this algorithm is effective in maintaining the integrity of the whole system, but many critics worry about what will happen if 51% of the users' cheat. This topic is out of the scope of my paper, but can be an interesting topic to research about.

On the other hand, cryptocurrency become vulnerable while trading. Bitcoin can be stolen through wallets or exchange, and by February 2014, it was revealed that $450 million worth of Bitcoins were stolen from Mt. Gox which shut down the exchange. Recently, there has also been a hack that stolen $31 million worth of Bitcoin. However, according to Justina Lee, these attacks does not prevent more consumers from entering this market. First, the price of Bitcoin experienced a small shock, which dropped from $8300 to $7800, but it soon went back up.

Current Cryptocurrency Market

Bitcoin was initially popular in part because its anonymity enabled trade in illegal goods. In October 2013, the US government shut down the largest website facilitating such trades. After that, though Bitcoin's price continued to climb, its price fluctuates more due to speculation, security problems, and general uncertainty about the technology.

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[3] More details on the current state of Bitcoin in the next section "Current Cryptocurrency Market"

Meanwhile, more cryptocurrencies are being introduced in the ecosystem. Almost all other cryptocurrencies were based on the Bitcoin protocol. They fix Bitcoin's shortcomings, while providing alternatives for consumers, which is why they are called *altcoins*, cryptocurrencies that are alternatives to Bitcoin. While some altcoins are better versions of Bitcoin, some do not provide any improvement over Bitcoin. This is because there is virtually no barrier to entry in the market, since Bitcoin is an open-source protocol, and new comers can still capture significant profits from their short lived period.

Many critics express concerns that Bitcoin will deflate heavily due to its limited supply. To be specify, Bitcoin's system only allows miners to mine Bitcoin at the decreasing rate, and eventually capped at 21 million coins, which is similar to the rate at which gold is mined. This intensify worries that as Bitcoin's price gets so high, it will lose its transactional value, network gains, … In the case of gold when the US was a colony, gold was replaced silver coins, its inferior goods. If we apply this to the current state of Bitcoin, Bitcoin's alternatives are more so its superiors, since they are improvement on the Bitcoin's protocol and come with lower cost to own. Therefore, this analogy suggests that as Bitcoin deflate significantly, it is likely that Bitcoin will be replaced by its alternatives.

However, current literature disagrees on this issue. Gandal et al argued that Bitcoin will eventually loses its dominant role due to its limited structure and other superior coins will take over. Meanwhile, other researchers believed that Bitcoin will remain the dominant player in this market because its first mover advantage is really significant.

Therefore, we want to learn more about how these coins are behaving in regard to one another. Cheah et al, as well as almost all Bitcoin researchers, confirmed that Bitcoin exhibits extremely speculative nature and has no fundamental value. However, if we treat these cryptocurrencies as "money or currency", then money's intrinsic value is calculated on its transactional demand. The Macro Note section elaborates more on demand for money.

Macro Note: Money Demand

In the discussion *The Transaction Demand for Money: A Close Look*, Kari summarizes the two main reasons why people would hold money, which can be translated into why people would hold Bitcoin if we treat Bitcoin as “money”.

People want to hold money because they need it to purchase goods and services with the cost that they have to compromise the potential interest they would have gained if they were to put that money in a saving account. Transactional demand for money depends on *interest rate* (if interest rates are low, then it is not worth it to move out of money into other assets and then back to money, and vice versa), *aggregate income* (if the volume of income and output produced in the goods markets increase, then the number of transactions and exchanges increase, and consequently, people would want to hold more money to perform their transaction promptly), and *price level* (if price increases, people will need to hold more money to support their given level of transactions).

In addition to transactional demand, speculative demand encourages consumers to hold money. This goes back to the asset market concept in macroeconomics. Suppose that interest rates fluctuate. At two percent a person can get $1020 in a year’s time in exchange for $1000 in cash now. However, they expect the interest rate to rise to ten percent, and as a result instead of $1020, they will make up to $1100 if they make the investment. So if interest rates are unusually low, and it is expected to rise, rational consumers would keep their wealth instead of holding on to cash to profit.

Bitcoin as “money”

Though cryptocurrencies are distributed through a decentralized system and have slightly different attributes than money, they still share some similarities in terms of why people wants to hold on to them: purchase power and speculation. According to Schuh and Shy, while many consumers who own cryptocurrencies use them to either make payments for goods and services (evidence for transaction demand), they also expect the currency to appreciate (speculative demand). As a result, we modeled demand for Bitcoin as “money” to learn more about how they are interacting with one another. Cianan et al attempted to model Bitcoin using the traditional market forces and Bitcoin’s attractiveness for investors, and these factors appeared to have a significant impact on Bitcoin price with variation over time. My research project will elaborate more on their method, but adding some proxies for other currencies to observe their interactions.

First, to model Bitcoin as a currency, we tried to look at Bitcoin's traditional determinants such as supply and demand. Ciaian et al (2016) modeled Bitcoin price formation similarly to gold. They denominate the stock of money base of Bitcoin in dollars for their research assuming that users have to convert everything to the dollars when they pay for goods and services. According to them, the Bitcoin money supply is the product of the total stock of Bitcoin in circulation and its price (dollar per unit of Bitcoin), and demand for Bitcoin is assumed to depend on the general price level, the size of Bitcoin economy, and the velocity of Bitcoin is circulation. They derived that in perfect markets, the equilibrium price is negatively correlated with the velocity and the stock of Bitcoin, while positively correlated with the size of Bitcoin economy and general price level.

Speculative demand for Bitcoin, or in Ciaian's words, attractiveness to investors and users is proved to be a significant driver of Bitcoin demand. A research done by Lee (2014) confirmed that news affect price of Bitcoin depending on the type of news (positive news increases price, while negative news decreases it). Therefore, we hypothesize that using Google search term for Bitcoin, we can capture the public attention to this currency. We might not be able to distinguish good vs bad news, but we believe this variable will be able to capture the speculative nature of Bitcoin's users. As Bitcoin gets more popular, more people will buy into it, hoping they can get a small profit out of the hype.

In addition to the Google trend, the Volatility Index (VIX), may be able to explain price of Bitcoin in some ways. Qadan and Yagil (2012) have found a connection between gold and the VIX between 1995 and 2010. The relationship between VIX and price of gold was negative. A higher VIX reflect a bearish condition in the exchange or the market as a whole, while a lower VIX reflects neutral to bullish condition in the exchange. Therefore, when VIX is low, we expect investors to invest more into assets like gold to hedge their investment. Similarly, since Bitcoin is not tied to any central fiat currency, investing in Bitcoin when the market is dull can be a decent strategy to diversify risk.

Bitcoin Futures

Figure 3: Bitcoin (USD) Price's turning point (coindesk.com)

In late December 2017, the Bitcoin Futures Exchange was open, giving BTC speculators another platform to speculate. Ever since, along with tightened regulation and manipulation from the BTC whales (a group of people that hold the largest shares of BTC), the price of BTC has been falling sharply. Despite some small increase in BTC price, its price, in general, decreased significantly ever since. Therefore, we want to further understand of how the factors of explaining BTC price will change their "role" along with this event.

Many critics argued that since BTC futures open, a lot of the speculation transitioned from the "real" exchange to the futures exchange, and therefore, we do not see as much speculative demand for BTC as we used to do before. According to Pylypczak-Wasylyszyn (2015), the Commodity Futures Trading Commission (CFTC), the government body responsible for futures market, classifies market participants as "commercial traders" to lock in pricing, or "non-commercial traders" or speculators in order words. While in agriculture and banking, it is popular to trade on futures market to ensure a stable price, speculation on futures is more for the purpose of directionally betting.

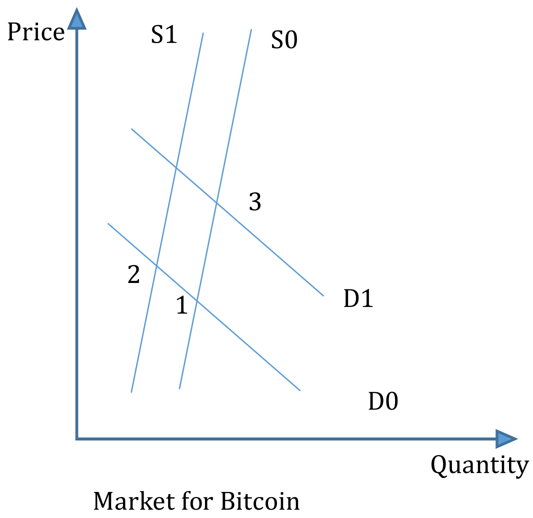
As traders always look for new ways to capitalize on the price movements of assets, and they are more interested in the price appreciation, than owning the commodity. Goods like gold and oil are extremely widely traded on these market. One example is that one investor may feel that gold offers better risk-to-reward profile during an economic downturn, so they would purchase gold futures to capitalize on that downturn. Therefore, as speculation for BTC continues to grow, investors can capture more profits from trading on BTC futures exchange, so the we may not see as much speculation on BTC as we did before.

As BTC price dropped tremendously, some economists argued that this is the “growing pain” of this currency. Optimists also believe that as the price decreases, and speculation wears off, we will be able to see more of its transactional demand more clearly.

3. Economics Model

Transaction Demand in Cryptocurrency Market

According to the Macro Note about Money demand, one of the reason why people would want to hold on to money is its purchasing power, or liquidity. Cash gives them the flexibility so that they can make almost any transactions with it. Similarly, previous literature demonstrated that there is evidence that people are holding cryptocurrencies in order to make payments and purchase goods and services with them. Fundamentally, we think this is one of the most important aspect of cryptocurrencies, introducing a new system of money and transaction that is not subject to any centralized authority. Considering this type of demand for cryptocurrencies, how the market behaves if we assumed people only want to buy cryptocurrencies to pay for goods.



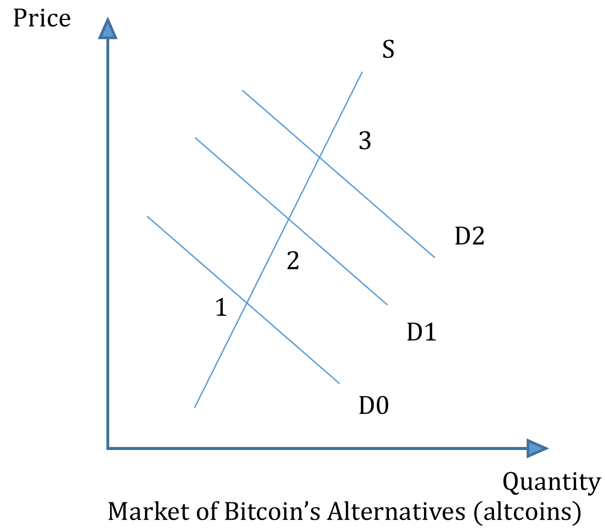
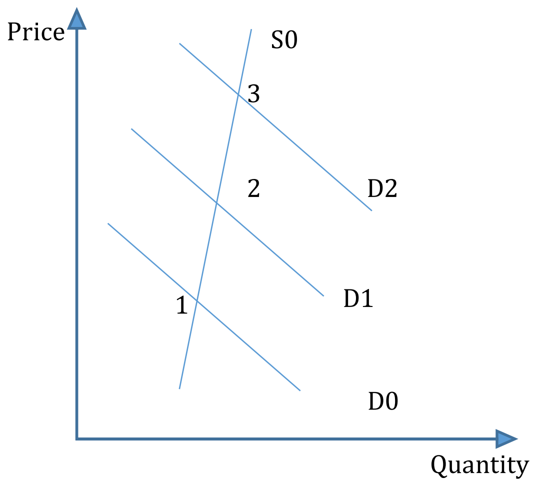


Figure 1. A breakdown of the current Cryptocurrency Market (Transaction Demand)
Hypothetically, price of Bitcoin increases (caused by a supply shock or something unexpected happened, S0 shifts to S1, point 1 to point2 in market for Bitcoin). The higher price in Bitcoin increases the demand for its alternatives.

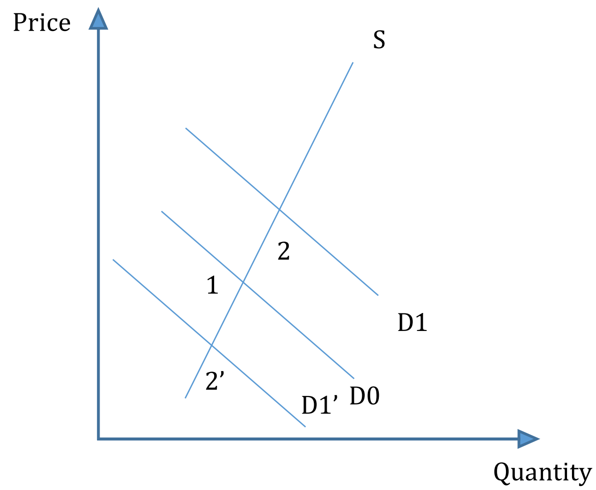
However, if demand of Bitcoin increases because there are more people flooding into the market (Demand for Bitcoin D0 shifts to D1, point 1 to point 3), this will prompt the consumers who already considered altcoins as Bitcoin alternatives to switch over to buy altcoins (Demand for Altcoin D0 to D2, point 1 to point 3). So overall, the price of Altcoins would also increase as well as their quantity.

Speculative Demand

This demand is put as people are interested in buying more Bitcoin because they think the returns will be lower if they were to buy other (financial) assets with their money. While this is a part of money demand, and helped explains why people wanted to hold money, similarly, Bitcoin, or cryptocurrency in this example. Due to the increase Bitcoin price, this demand has been growing exponentially large. In this model, we attempted to capture the relationship between Bitcoin and Altcoins assuming there is only speculative demand for them. (Most people who own Bitcoin expect it to appreciate in prices, and existing literature up until 2014, 2015 suggested that Bitcoin has an extremely speculative nature.)



Market for Bitcoin



Market of Bitcoin's Alternatives (altcoins)

Figure 2. A breakdown of the current Cryptocurrency Market (Speculative Demand)
Suppose people expect the price of Bitcoin to rise, they would be interested in holding Bitcoin to get some profits, as a result, demand for Bitcoin increases (D0 to D1, point 1 to point 2). As the supply of Bitcoin is increasing at a set rate by the algorithm, we assume supply does not change significantly in the short run. Therefore, the increase in price of Bitcoin would signal other consumers that price of Bitcoin will continue to grow, which create a feeding system for price and demand to grow in tandem of each other (D1 to D2, point 2 to point 3,…)

In the market of Altcoins, if we assume that people only hold on to cryptocurrencies for speculative purposes, and there's no new consumers in this market, the demand for altcoins would decreases because their buyers are putting their bets on Bitcoin. However, if there are more people entering the market to buy cryptocurrencies, since the price of Bitcoin is too high, and they might expect Altcoins to appreciate as well, demand for Altcoins can also increases. Therefore, the overall impact on the Altcoins' market is ambiguous in this argument.

Network effects

The network effect suggests that as the number of users of a network increases, its value increase. We use the analogy of Facebook and Google+, where Bitcoin is the existing player and alternative coins are Google+. What would happen, clearly, is that as the Bitcoin gets more popular, its demand will increase because of the network effect. As a result, its alternatives will likely to be neglected, since consumers do not see the value of holding other cryptocurrencies.

Below are my graphs with the assumption that the Bitcoin's network effect gives Bitcoin an advantage in the market.

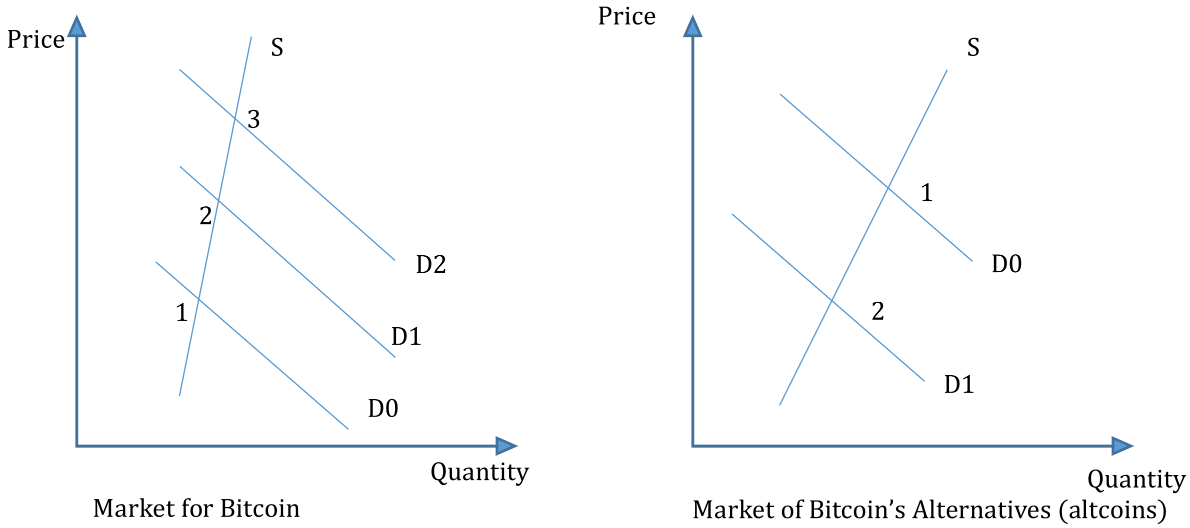


Figure 3. A breakdown of the current Cryptocurrency Market with the Network Effects
As Bitcoin gets more popular, its demand increases (since more people are joining the market), which shifts its demand curve from D0 to D1 (point 1 to point 2). As a result, its price increases, which caused more people wanting to own it. Again, its demand increases to D2 (point 2 to point 3), this cycle keeps feeding itself until people lose interest in Bitcoin, or they do not expect Bitcoin to appreciate anymore.

Meanwhile, the market for Bitcoin's substitute behaves in the opposite direction. As more people invest in Bitcoin, they do not see the point in buying other cryptocurrencies, since they do not expect them to appreciate as much as Bitcoin. Therefore, the demand for them decreases, which results in a drop in price for other cryptocurrencies.

However, when it comes to the network effects, what matters the most is the transaction ability of Bitcoin. Going back to the purpose of Bitcoin, it introduces a new decentralized system of payment, that does not require any central authority to approve payment or control money supply, but rather its cryptography technology. The previous literatures that examine the network effect of this market [2,3] did not address the different forces that driving demand, so we want to answer the question if the network effect of Bitcoin is large enough to give it the competitive edge compared to Altcoins, and if so, what demand that is driving this network effect for Bitcoin.

On the other hand, Gandal et al indicates that instead of the network effect, the fact that newer currencies are improvement upon Bitcoin's system can lead to a substitution effect in this market. Specifically, as price of Bitcoin goes up, consumers do not see the purpose of buying Bitcoin, so they decide to invest in other currencies with similar functionalities for cheaper price

More recent literature confirm that consumers are using Bitcoin and other cryptocurrencies to pay for goods and services and show evidence that cryptocurrencies can be useful in economic reasons such as trade transaction. Lewis (2017) suggested that while the rapid increase in Bitcoin's price is driven by speculative demand, but the demand for Bitcoin as a transaction tool is growing in tandem underneath it, and eventually, as the speculative demand wears off, we will be able to see more clearly how the transaction demand is determining Bitcoin's price.

4. Methodology

This model incorporates economic variables like supply and the price of substitutes of Bitcoin, as well as speculative variables that captures Bitcoin's attractiveness to investors like Google queries for Bitcoin. This model is a time-series regression specified as follows:

$$P_{BTC} = f\,(P_{ATC}, ECO, S_{BTC}\,, GLE, VIX, VOL, VEN, D_{FUT})$$

Where:

P_{BTC} = the price of Bitcoin in time t

P_{ATC} = the price of Bitcoin's alternatives like Ethereum, Litecoin, Ripple…

ECO = the size of Bitcoin's economy (number of transactions/addresses)

S_{BTC} = the supply of Bitcoin (number of coins in circulation)

GLE = the number of BTC queries on Google

VIX = the volatility index of the S&P 500

VEN = the number of vendors that accept Bitcoin as payment

D_{FUT} = a dummy on when the future exchange of Bitcoin is introduced

The signs are hypothesized below:

$$\begin{array}{l} \qquad\qquad\qquad\quad (+/-) \qquad (+) \qquad\quad (-) \qquad (+/-) \qquad (+/-) \quad (-) \qquad\quad (-) \\ PBTC = \beta 0 + \beta 1 PATC + \beta 2\, ECO + \beta 3 SBTC + \beta 4 GLE + \beta 5 VIX + \beta 6 VEN + \beta 7 DFUT \end{array}$$

Data Sources and Specifications

We want to incorporate the traditional supply and demand model to model Bitcoin. To simplify the model, we assume that users convert Bitcoin into dollars for transactional purposes (when in fact, they do not have to unless they trade Bitcoin with Dollar).

Data on the price of Bitcoin, as well as other cryptocurrencies that we are using in the model including Litecoin and Ethereum, can be found on Coinmetrics.io. The economy of Bitcoin, or number of transactions in Bitcoin, data is also retrieved from Coinmetrics.io. Coinmetrics claimed that this measure can be underestimated. For example, in case when one sender sends BTC to many receivers, that should be translated to multiple transactions, but it only recorded one transaction. The data on supply of Bitcoin is also from this website. Coinmetrics defined it as “the number of new coins that have been brought into existence on that day”, and they claimed this is not an estimate number, but rather the actual amount of Bitcoin in circulation.

In addition, to capture attractiveness to investors, we use Google search queries for Bitcoin term. Since Google indexed their data after 90-day period, we need to convert it to real term.

VIX is the proxy we use to measure Bitcoin’s speculative demand. In 2017, the price of Bitcoin skyrocketed despite critics and comparisons to the Tulip maniac… However, when the price dropped recently, with the introduction of Bitcoin future exchange, investors were more cautious toward this cryptocurrency, so we want to test if the launch of Bitcoin future affect the way investors spend their money on this currency. We suspect rather than “blind” speculation from the crowd, the professional investors will establish their systematic way of thinking, and make the VIX significantly explain the volatility of Bitcoin’s price.

As an effort to capture transactional demand for Bitcoin, we are interested in seeing how the increases of vendors accepting Bitcoin affect Bitcoin's demand, and number of vendors accepting Bitcoin might help in explaining it. The data we obtained from coinmap.org. The only problem is that we cannot see how many vendors stop accepting Bitcoin, but we will use this data until we can find a better dataset.

Model Specification

Since this is a time-series analysis, we need to consider for the serial correlation. After running the Durbin-Watson test on the variables, we can see that these measures are highly non-stationary, especially price series, and therefore, to avoid spurious regression, we decided to run a dynamic double-log regression to mitigate the serial correlation.

$$\begin{aligned}\ln PBTC = {} & \beta_0 + \beta_1 ETH_t + \beta_2 LTC_t + \beta_3 ECO_t + \beta_4 SBTC_t + \beta_5 SEARCH_t + \beta_6 ATTACK_t \\ & + \beta_7 VIX_t + \beta_8 VEN_t + \beta_9 D_{FUT} + \beta_{10} PBTC_{t-1} + \varepsilon\end{aligned}$$

Ssekuma (2011) suggested that cointegration regression is one of the most robust model to for time-series data. After running the dynamic model, we also employ the Pesaran cointegration to better understand Bitcoin's price movement in the short and long run. The short-run Bitcoin cointegration model is specified as follows:

$$\begin{aligned}\Delta P_{BTC} = {} & \alpha_0 + \sum_{i=0}^{n} \beta_i \, \Delta PETH_t + \sum_{i=0}^{n} \gamma_i \, \Delta PLTC_t + \sum_{i=0}^{n} \delta_i \, \Delta ECO_t + \sum_{i=0}^{n} \eta_i \, \Delta SBTC_t \\ & + \sum_{i=0}^{n} \vartheta_i \, \Delta SEARCH_t + \sum_{i=0}^{n} \kappa_i \, \Delta ATTACK_t + \sum_{i=0}^{n} \mu_i \, \Delta VIX_t + + \sum_{i=0}^{n} \nu_i \, \Delta VEN_t \\ & + \alpha_1 D_{FUT} + \lambda_1 \Delta ETH_t + \lambda_2 \Delta LTC_t + \lambda_3 \Delta ECO_t + \lambda_4 \Delta SBTC_t + \lambda_5 \Delta SEARCH_t \\ & + \lambda_6 \Delta ATTACK_t + \lambda_7 \Delta VIX_t + \lambda_8 \Delta VEN_t + \varpi\end{aligned}$$

The short-run model transformed the independent variables into differenced natural logs and includes the error correction variable. The long-run model is determined using the logs of the variables, allowing for the interpretation of the determinants' elasticities.

$$\ln PBTC = \beta_0 + \beta_1 \Delta ETH_t + \beta_2 \Delta LTC_t + \beta_3 \Delta ECO_t + \beta_4 \Delta SBTC_t + \beta_5 \Delta SEARCH_t + \beta_6 \Delta ATTACK_t + \beta_7 \Delta VIX_t + \beta_8 \Delta VEN_t + \beta_9 D_{FUT} + \varepsilon$$

Since BTC prices, similarly to gold prices or interest rates, are non-stationary (more information in the Appendix), a co-integration model has been proved to better account for the non-stationarity of the variables compared to others such as linear or dynamic regression.

5. Results

Dynamic Double-log Model

The first model that was run and tested was the 2015-present dynamic double-log model, which aimed to understand the effects of the independent variables on the price of Bitcoin since 2015. The results of the regression are outlined in Table 1.

Table 1: Dynamic Double-log Regression Results

Variable	Coefficient	p-value
ln (BTC price) lagged	0.9351101***	0.000
ln (ETH price)	-0.0049201*	0.020
ln (LTC price)	0.0287385***	0.000
ln (ECO)	0.035971***	0.000
ln (SBTC)	0.0098351	0.159
ln (GG search)	0.0021403	0.535
ln (Cyber-attack)	-0.0010265	0.272
ln (VIX)	-0.0081345	0.241
ln (VEN)	0.3107097***	0.000
D_{FUT}	-0.037118***	0.000
(Intercept)	-2.89154***	0.000
R^2 = 0.999		
Adjusted R^2 = 0.999		
Df = 950		
Significance Codes: ***0, **0,001, *0.05, . 0.1		

As the results of the initial regression demonstrated, variables including the lagged BTC price, ETH price, LTC price, ECO (number of transaction in BTC), VEN (number of vendors), and D_{FUT} are highly significant, and the adjusted R-squared is 0.999. These results show us that the independent variables account for a 99.9% of the BTC price variance.

Moreover, ECO, VEN, and D_{FUT} have the expected signs. The ECO coefficient means that for every marginal percent increase in transaction in BTC, the price of BTC increase by 0.03%, all others equal. The VEN coefficient means that for every marginal percent increase in Google Trends Index, the price of BTC increase by 0.002%. The D_{FUT} coefficient means that since the introduction of the BTC futures exchange, the price of BTC experienced a drop of 0.03% in general. It is also important to stress that, this dummy variable not only measure the effects of BTC futures on BTC price, but also a combination of events including tightened regulations and manipulations,…

While GG search, Cyber-attack, and VIX are insignificant, they have the expected signs. The GG search coefficient indicates that a percent increase in Google Trend Index leads to 0.002% increase in BTC price. The Cyber-attack coefficient signifies that one percent increase in Google Trend Index for cyber-attack leads to 0.001% decrease in BTC price. Since BTC or other currencies are based completely on software, this result agrees with our hypothesis that as people lose trust over cyber security, they also do not believe in the power of BTC as much as they did before.

The VIX coefficient also demonstrated that one percent increase in VIX index, the price of BTC decreases by 0.008%. Since a climbing VIX reflects a bearish condition in the exchanges, or the market as a whole, investors, which means that volatility decreases, and prices are expected to depreciate, according to Yang and Doong (2004).

Considering the coefficient of ETH and LTC price. A negative coefficient of ETH price signifies a substitute relationship between ETH and BTC, as ETH price increases by one percent, BTC price decreases 0.0049 percent. A positive coefficient of LTC price signifies a complementary relationship between BTC and LTC, as LTC price increases by one percent, BTC price also increases by 0.028 percent.

Though most of the independent variables are significant and have the expected signs, there are a few things that is problematic about this regression. The high adjusted R-squared may suffer from inflation due to misspecification, multicollinearity, or autocorrelation. The Aikaike Information Criterion (AIC), Ramsey Regression Equation Specification Error Test (RESET), and Durbin-Watson test, as well as the Variance Inflation Factors (VIF) were implemented to test for these potential errors. A full table of the diagnostic results can be found in the Appendix.

The AIC measures the quality of the model fit to the data (Studenmund 2010). To interpret the AIC, the model of minimum AIC value is the better-fitting model. While there is no hypothesis to test, this model determines the better-fitting model relative to other with the same data.

The RESET test's null hypothesis is that a model does not suffer from misspecification or omitted variables. The RESET test statistic of 6, and p-value of 0.0005 rejects this null, and indicates that this model suffers from omitted variable or misspecification. Therefore, the coefficients of the independent variables are not reliable to interpret.

The Durbin-Watson tests for serial correlation, which is when the variables from a previous time (lagged variable) affect the dependent variable of the current time period (Studenmund 2010). Time-series model is usually subject to this errors, especially when it comes to supply and demand, because expectations play a vital role in the model. The null hypothesis for the Durbin-Watson test is that there is no serial correlation, and our test statistics returns 1.938 falls in the inconclusive region of the distribution.

Multicollinearity is also another problem in this regression, since we have a VIF statistics of 23.95. However, multicollinearity is unavoidable in time-series dynamic regression, and a VIF of 23.95 is relatively low compared to other empirical time-series model.

Cointegration Model

The Dickey-Fuller test on price series confirms that BTC, ETH, and LTC prices are all non-stationary. To account for the non-stationary, a cointegration regression is conducted to better model the data as well as further understand the underlying relationship between dependent and independent variables.

We estimate the long-run partial elasticities of the price of gold with respect to each independent variable (Table 2), and the short-run in Table 3, using the Error Correction Model (ECM). In ECM, the movement of any one determinant in time t, is related to the gap in time t-1 from its long-run equilibrium.

Table 2: Long-run Elasticities, 2015-Present

Variable	Coefficient	p-value
lETH	0.01338124	0.6356
lLTC	0.2464411***	0.0003
lECO	0.4402868**	-0.0016
lSBTC	-0.0337608	-0.6977
lGG	0.1504677***	0.0000
lCYBER	0.01933748	-0.1129
lVEN	3.396127***	-0.0001
lVIX	-0.0850465	-0.3592
DFUT	0.2039283*	-0.0497
(Intercept)	-30.09134***	0.0001
R^2 = 0.429		
Adjusted R^2 = 0.406		
Df = 915		
Significance Codes: ***0, **0,001, *0.05, . 0.1		

Table 2 shows the long-run elasticities between the price of gold and its determinants. Other than the Cyber-attack and DFUT variable, all of the coefficients have the expected signs. LTC, ECO, GG, VEN are significant at 0.1% level. However, price of ETH, which is positive and inelastic, is not significant, can be understandable. This may be because the purpose of the two blockchain systems are different. Bitcoin was created to serve as a currency, while Ethereum is more for the building application on the blockchain system purpose.

On the other hand, LTC price is significant and inelastic with a one percent increase leads to 0.246%, holding all others equal. LTC coefficient is also highly significant, which implies a long-run relationship with BTC. Researching more into LTC, we also found that LTC has existed almost as long as BTC has, and its developers tend to replicate the peer-to-peer payment system of BTC. That explains why LTC price is so significant in explaining BTC price in the long-run.

ECO, or transactions in BTC is also positive and inelastic, yielding for one percent increase in transaction, price of BTC increases by 0.44%. SBTC returns negative and inelastic, for every percent increase in the supply of BTC, its price decreases by 0.034%. Number of vendors accepting BTC, VEN, is elastic and positive, implying that for every percent increase of vendor accepting BTC, its price increase by 3.39%. While all these variable capturing BTC transactional demand are significant, we are most skeptical of the VEN variable. While ECO and SBTC measure the traditional element of the BTC market, VEN may also capture some of the speculative demand. This can be because some of the vendors want to speculate BTC to earn profit from the price appreciation rather than wanting to keep BTC as their assets.

GG search is positive and inelastic. To be specific, for every percent increase in Google Trend Index of Bitcoin, the price of BTC increase by 0.15%. However, search for Cyber-attack variable is not significant, and in fact, positive and inelastic. This implies that overall, people does not really care about cyber-attack, but rather its popularity when investing in BTC. As BTC gets more popular, its price also appreciates tremendously, which is why investors decide to spend their money to capture future profit.

Lastly is the VIX variable, though it is not significant, it is negative and inelastic. Recall BTC's price increase from 2015 to late 2017 despite any economic condition or political scrutiny. Does this variable tell us that BTC speculators pour money into it, because they believe this decentralized payment system is not subject to any economic down/upturn?

Table 3: Error-Correction Model and Short-run Elasticities, 2015-Present

Variable	Coefficient	p-value
Δln BTCt-4	-0.0641177	0.0439
Δln ETHt	0.0989996***	0.0000
Δln LTCt	0.3382258***	0.0000
Δln ECOt-5	0.0265963**	0.0034
Δln SBTCt-3	0.023515*	0.0112
Δln GGSt-6	0.0181151***	0.0011
Δln CYBERt-4	0.0005099	0.7493
Δln VIX t-2	-0.0309688	0.0363
Δln VENt	4.7006253**	0.0023
DFUT	-0.0103911**	0.0048
ecm1	-0.010972	0.2344
(Intercept)	0.0009281	0.58643
R^2 = 0.3971		
Adjusted R^2 = 0.3782		
Df = 923		
Significance Codes: ***0, **0,001, *0.05, . 0.1		

In this model, only the most significant variable in each category is kept, and they are the 4th lag of the price of BTC, the price of ETH and LTC, the 5th lag of ECO, the 3th lag of SBTC, the 6th lag of GGS, the 2nd lag of VIX, and the VEN.

The result shows that with the introduction of the error-correction term, other than CYBER, all the other variables are still significant, which is consistent with other models. The coefficient of SBTC is also unexpected, implying a positive relationship between BTC supply and BTC price. The fact that we are including both supply and demand for BTC in one equation may be the cause of the unexpected sign. However, for the short-run period, price of BTC may not have enough time to settle at an equilibrium point yet, so the relationship is positive.

The error-correction coefficient indicates a 1.097% adjustment in one day. To diagnose this model, we conducted several tests as following:

- The Wald test determines the true value of parameters in the data based on the sample estimate. If the parameter is 0, there is no relationship between them (Fears, Benichou, and Gail 1996). The Wald test rejected the null hypothesis that the relationship parameters are zero, implying that cointegration exists in the model.

- The Breush-Godfrey test for serial correlation in the residuals. This test is similar to Durbin-Watson, but it is more robust, since it is not limited to nonstochastic regressors. Unfortunately, both of the tests failed to reject the null hypothesis that serial correlation exists.

- Jarque-Bera test for normality, kurtosis, and skewness of the model's fit (Jarque and Bera 1987). This test rejected the null that skewness and kurtosis are zero.

- Augmented Dickey-Fuller test to determine the unit root. If the null hypothesis of unit root equals zero is rejected, then the series is determined to be integrated. The test returns marginally significant results. We can reject the null at 5% level of significance, but not 1%. Therefore, the model is stationary to some extent.

- The Ramsey RESET test is also carried out to test for misspecification error, and the test result rejects the null that there is no misspecification error.

6. Conclusion

Ever since the introduction of Bitcoin, the first ever decentralized payment system, it has attracted attention from the media and investors, especially when it comes to what is driving Bitcoin price. As we are trying to better understand the underlying relationship between Bitcoin and two of its runner-ups, we are able to learn more about the different drivers of Bitcoin's demand including transactional and speculative demand.

Consistently with many critics, demand for Bitcoin is driven mostly from unconventional indicators like media attention or price of another cryptocurrency. In the analysis, the price of Ethereum proved to be significant in explaining the variance in Bitcoin's price in the short-run error-correction model, but less significant in the dynamic double-log model, and then insignificant in the long-run elasticities model. This may happen because the original purpose of the two blockchain systems are different. While Bitcoin's developers envision a decentralized payment system, Ethereum's developers are looking toward a blockchain system that software engineers can build more applications upon.

While Ethereum's investors may not have the same interest as Bitcoin's investors, Litecoin's investors may. Through the three models, price of Litecoin consistently positively correlated with price of Bitcoin. Going back to the developers' intention, both of these cryptocurrencies are expected to serve the main purpose of a decentralized payment system. In another word, according to my economics model, Litecoin may be a substitute for Bitcoin. Therefore, this market does not really exhibit a strong network effect, and with more runner-ups like Litecoin, Bitcoin is facing some serious competitions from newer cryptocurrencies for its dominant player role.

The Dummy of Bitcoin futures exchange is also significant in all three models, implying that there is, in fact, a structural break in late December 2017. This dummy actually accounts for a lot of events happening around this time. Not only the introduction of Bitcoin futures, but also the tightened regulations, the shut-down of some well-known cryptocurrencies exchange, the ban of cryptocurrency in China, the manipulation of Bitcoin whales,… eliminates speculation for Bitcoin. The sign of this coefficient is consistent with the current news.

One of the main factors why Bitcoin speculation decreases significantly can be caused by the Bitcoin whales, and regulations. Bitcoin whales are the largest Bitcoin holders in the community, and they also know one another, and have access to all of the whales' activities. Some cryptocurrencies traders commented that these whales are selling off their shares to avoid regulations from the government. In addition, this massive sell-off will prompt "outside" people to think that Bitcoin speculation is gone, so that eventually they will start to trade with one another again to create another Bitcoin maniac to profit from. Our result is consistent with this theory, but we doubt that Bitcoin price will ever get as high as it did before, since so many newer coins with advanced functionalities have been introduced, and as we can see from the Litecoin's example, Bitcoin's network effect is not that significant to keep its place for a long time.

Acknowledgement

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Appendix

1. Correlation matrix

	BTC	ETH	LTC	ECO	SBTC	GGS	CYBER	VIX	VEN
BTC	1								
ETH	0.9451	1							
LTC	0.9611	0.9131	1						
ECO	0.5257	0.5465	0.3583	1					
SBTC	-0.6193	-0.6603	-0.4921	-0.5307	1				
GGS	-0.3641	-0.3693	-0.3903	-0.0524	0.2223	1			
CYBER	0.2278	0.2414	0.1998	0.1448	-0.0491	-0.1018	1		
VIX	-0.4833	-0.5288	-0.3813	-0.6134	0.5911	0.2228	-0.1304	1	
VEN	0.9824	0.9389	0.9369	0.4917	-0.6586	-0.4018	0.2215	-0.4361	1

2. Dynamic Double-log Diagnostics Table

Test Type	Coefficient	p-value
AIC	-3475.001	n/a
Durbin-Watson	1.938932	
RESET Test	6	0.0005
R-squared	.999	
Adjusted R-squared	.999	

VIF	
ln (BTC price) lagged	101.05
ln (ETH price)	75.95
ln (LTC price)	32.53
ln (ECO)	13.93
ln (SBTC)	4.17
ln (GG search)	3.6
ln (Cyber-attack)	3.01
ln (VIX)	2.54
ln (VEN)	1.61
DFUT	1.14
Mean VIF	**23.95**

3. Short-run Error Correction Diagnostics

Test	Test Statistic	p-value
Wald	6.575	0
Durbin-Watson	1.919	0.103
Breush-Godfrey	1.0514	0.3796
RESET	66.071	0
Jarque-Bera	62.859	0
Augmented Dickey-Fuller	-5.1869	0

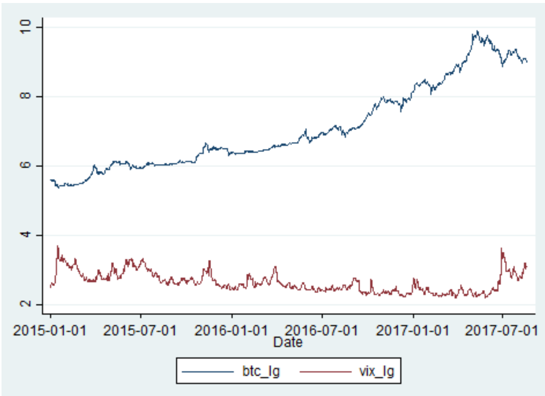
4. Dickey-Fuller results of logged variables

Dickey-Fuller		
Variable	**Test statistic**	**p-value**
ln (BTC)	-0.108	0.9486
ln (ETH)	-0.933	0.7768
ln (LTC)	0.337	0.979
ln (ECO)	-7.586*	0
ln (SBTC)	-5.757*	0
ln (GG search)	-2.937*	0.0412
ln (Cyber)	-7.402*	0

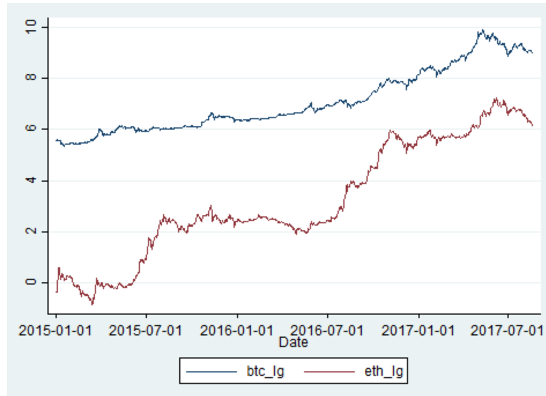
ln(VIX)	-3.65*	0.0049
ln(VEN)	15.81	1

(*) indicates that the variable is nonstationary

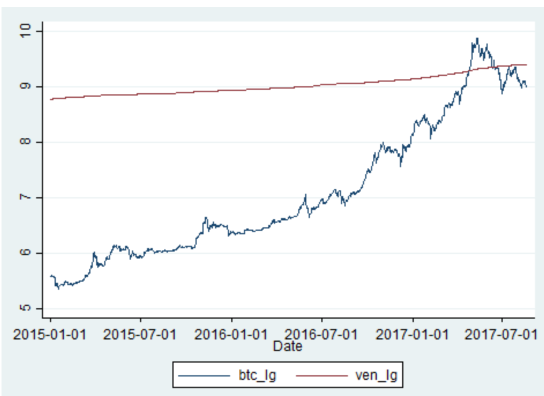
5. Graphs



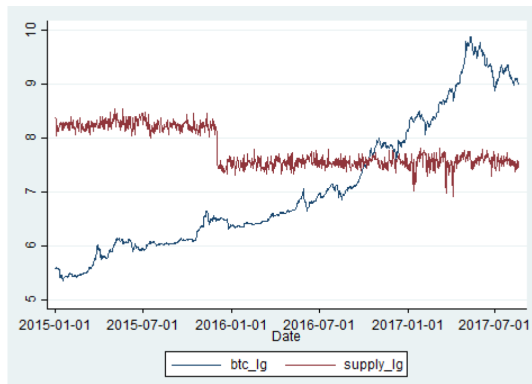
5.1. ln BTC vs ln VIX



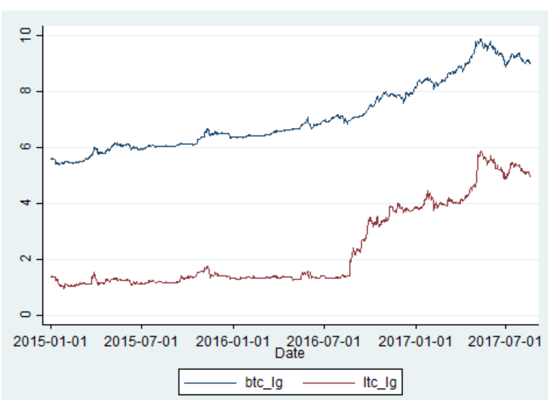
5.2. ln BTC vs ln ETH



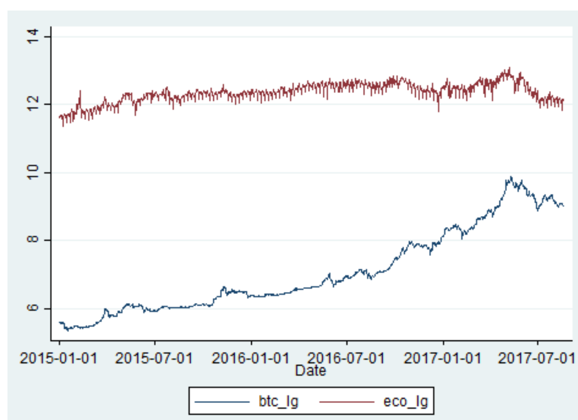
5.3. ln BTC vs ln VEN



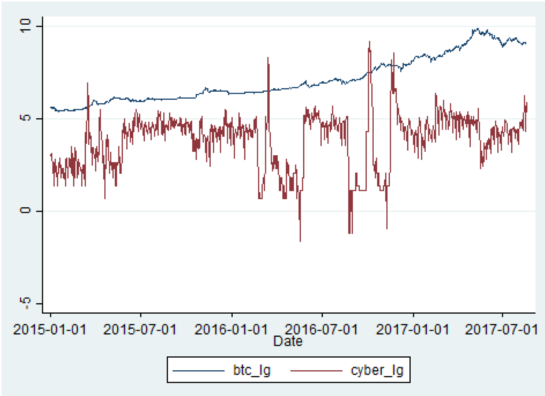
5.4. ln BTC vs ln SBTC



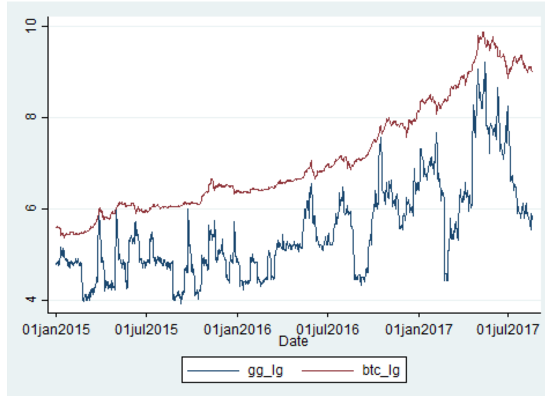
5.5. ln BTC vs ln LTC



5.6. ln BTC vs ln ECO



5.7. ln BTC vs ln CYBER



5.8. ln BTC vs ln GG Search

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