

Stanford University
Masters Thesis


CAN WE PREDICT THE RETURNS OF CRYPTO-CURRENCIES?

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Abstract

In this thesis I investigate the extent to which we can predict the market outcomes of cryptocurrencies. I focus on the two currently most prominent cryptocurrencies: Bitcoin and Ethereum. In the first part of the thesis I investigate whether the price levels of Bitcoin and Ethereum satisfy the weak form of the Efficient Market Hypothesis. I find evidence of weak-form efficiency in the market for cryptocurrencies. In the second part of the thesis I ask whether cryptocurrencies are viewed as an hedging vehicle against the mainstream economy. To answer this question I explore the association between market outcomes for Bitcoin and Ethereum and the Yield Curve. I find limited evidence of an association between the cryptocurrencies market and the Yield Curve. In the third part of the thesis I ask whether the market for cryptocurrencies is driven by noise traders. To answer that I explore the association between market outcomes for cryptocurrencies and qualitative information from Google searches. I find evidence of strong predictability of the price and transaction volume of Bitcoin by indexed Google searches, suggesting that the fashionability and popularity of Bitcoin go hand in hand.



Susan Athey, The Economics of Technology Professor, Stanford GSB
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Contents

1	Introduction	4
2	Background on Bitcoin	6
3	Background on Ethereum	9
4	Data and Descriptive Statistics	11
5	Efficient Market Hypothesis	19
5.1	Autocorrelations and Partial Autocorrelations	21
5.2	Testable Hypothesis	24
5.3	Statistical Tests	24
5.3.1	Tests of White Noise	25
5.3.2	Ljung-Box Test	27
5.3.3	Runs Test	27
5.3.4	Bera-Jarque Test	28
5.3.5	Augmented Dickey-Fuller Test	29
5.4	Results	30
6	Is demand for cryptocurrencies pro-cyclical?	31
6.1	Empirical Investigation	31
6.2	Results	32
7	Can Google searches predict the Cryptocurrencies' market?	33
7.1	Empirical Methodology	34
7.2	Results	35
8	Conclusion	44

List of Tables

1	Summary Statistics	13
2	Ljung-Box Test of White Noise for Bitcoin	27
3	Ljung-Box Test of White Noise for Ethereum	27
4	Runs Test for Bitcoin	27
5	Runs Test for Ethereum	28
6	Bera-Jarque Test of Normality for Bitcoin	28
7	Bera-Jarque Test of Normality for Ethereum	28
8	Augmented Dickey-Fuller Test for Bitcoin	29
9	Augmented Dickey-Fuller Test for Ethereum	29
10	Augmented Dickey-Fuller Test for Bitcoin: Multiple Lags	29
11	Augmented Dickey-Fuller Test for Ethereum: Multiple Lags	30
12	The Association between the Yield Curve and Returns to Bitcoin	33
13	The Association between the Yield Curve and Returns to Ethereum	33
14	The Association between the Google Searches and Bitcoin: No Lags	36
15	The Association between the Google Searches and Bitcoin: 3 Lags	37
16	The Association between the Google Searches and Bitcoin: 6 Lags	38
17	The Association between the Google Searches and Bitcoin: 12 Lags	39
18	The Association between the Google Searches and Ethereum: No Lags	40
19	The Association between the Google Searches and Ethereum: 3 Lags	41
20	The Association between the Google Searches and Ethereum: 6 Lags	42
21	The Association between the Google Searches and Ethereum: 12 Lags	43

List of Figures

1	Time Series of Bitcoin log(Price)	14
2	Time Series of Bitcoin Yield	14
3	Time Series of Ethereum log(Price)	15
4	Time Series of Ethereum Yield	15
5	Time Series of 10-Year Bond	16
6	Time Series of 3-Month Bond	16
7	Time Series of Difference between 10-Year and 3-Month Bond Yield . . .	17
8	Kernel Density of Bitcoin Returns	18
9	Kernel Density of Ethereum Returns	18
10	Auto-correlation of Bitcoin Yield	22
11	Partial Auto-correlation of Bitcoin Yield	22
12	Auto-correlation of Ethereum Yield	23
13	Partial Auto-correlation of Ethereum Yield	23
14	Tests of White Noise of Bitcoin Yield	26
15	Tests of White Noise of Ethereum Yield	26

1 Introduction

Cryptocurrencies have received great attention by investors in the recent years. The most well-known crypto-currency is Bitcoin. Bitcoin has received substantial attention because of its innovative features, simplicity, transparency and its increasing popularity. Bitcoin was first outlined in a paper by [Nakamoto et al. \(2008\)](#) and went online in 2009. The price of Bitcoin has increased by over 5000% up July 2016. Bitcoin has been used as means of trade and store of value, as well as an investment vehicle with [Selgin \(2015\)](#) and [Baek and Elbeck \(2015\)](#) arguing that Bitcoin should be seen as a speculative commodity rather than a currency. Yet, the efficiency of Bitcoin or any other cryptocurrency within the meaning of [Malkiel and Fama \(1970\)](#) has not been fully investigated in the recent years. In the context of an asset market, efficiency means predictability. An efficient market exhibits low predictability. [Urquhart \(2016\)](#) have investigated the efficiency of Bitcoin only up to the end of July 2016. In this thesis, I expand the time window of investigation of market efficiency to include more recent observation and extend the research question of predictability to another prominent cryptocurrency, Ethereum. Bitcoin and Ethereum are the two gate cryptocurrencies in the meaning that the myriad of other cryptocurrencies currently available are only tradable with Bitcoin and Ethereum and not directly (or as easily) exchangeable with hard (fiat) currencies like USD or Euro. For investors to buy less-known cryptocurrencies they need to buy Bitcoin or Ethereum first in order to exchange them for other cryptocurrencies. Because of their role as a means to enter and exit the cryptocurrencies market, Bitcoin and Ethereum can be viewed as reflecting the behavior of the whole market of cryptocurrencies.

The efficient market hypothesis (EMH) is one key cornerstone of financial economics, first developed by [Malkiel and Fama \(1970\)](#). A market is said to be efficient if prices fully reflect all available information. [Malkiel and Fama \(1970\)](#) distinguishes between

three forms of market efficiency with the most commonly examined form being the weak form. A market is said to be weak form efficient if investors cannot use past information to predict future returns. The weak form EMH has been studied extensively in the literature for many traditional financial assets and commodities ([Kristoufek and Vosvrda, 2014](#)). The efficiency of Bitcoin has been studied by [Urquhart \(2016\)](#), however Ethereum has so far been unexplored.

The literature on cryptocurrencies was primarily dominated by studies on the safety, legal and ethical aspects of cryptocurrencies, although recent studies have examined cryptocurrencies from an economic standpoint. [Fry and Cheah \(2016\)](#) claim that if Bitcoin were a true form of store of value, or a true unit of account, it would not display such volatility demonstrated by bubbles and crashes.

[Dwyer \(2015\)](#) concludes that the average monthly volatility of Bitcoin is higher than that for commodities like gold or a set of currencies, and the lowest monthly volatilities of Bitcoin are less than the highest monthly volatility for gold and currencies. [Cheung et al. \(2015\)](#) demonstrates the existence of short-lived bubbles, but also three huge bubbles in the Bitcoin market over the studied period. The last big bubble of Bitcoin led to the demise of the Mt Gox exchange. [Briere et al. \(2015\)](#) find that Bitcoin offers significant diversification benefits for investors while [Dyhrberg \(2016\)](#) conclude that Bitcoin has similar hedging capabilities as gold and the USD, and as such can be employed to reduce portfolio risk. [Fry and Cheah \(2016\)](#) develop an econo-physics model to show that Bitcoin and another cryptocurrency, Ripple, are characterized by negative bubbles. Even though public policy rarely gets involved in the financial markets, the level of efficiency in the cryptocurrencies market determines the degree to which a level can be influenced or manipulated, which is usually regulated by institutions like the U.S. Securities and Exchange Commission.

2 Background on Bitcoin

In October 2008, Bitcoin's inventor Satoshi Nakamoto published a paper¹ that outlined a fully functional cryptocurrency.² This cryptocurrency could be used for financial transactions (sending and receiving value) in a system that is completely decentralized and operates in a manner that is not based on trust. Since then, the Bitcoin network has continued to expand and evolve to meet the needs of its users. In this section, I discuss some of the important milestones in Bitcoin's history.

Bitcoin is the original cryptocurrency and many of its firsts reflect the firsts for cryptocurrencies in general. In August (18), 2008, the domain bitcoin.org was registered. Since it is not known when Satoshi Nakamoto began developing the concepts of the blockchain and cryptocurrency, this is the first public indication of Bitcoin's creation. By this point, Satoshi possibly had a functional design for a cryptocurrency but was finalizing details and working on writing up the technical paper description of the Bitcoin protocol.

On October 31, 2008, Satoshi Nakamoto released his technical paper "Bitcoin: A Peer-to-Peer Electronic Cash System" to The Cryptography Mailing List. This paper provided a full description of how Bitcoin would work and the first description of the blockchain, the underlying technology that makes cryptocurrency possible.

On January 3, 2009 Satoshi mined the genesis block of Bitcoin. A cryptocurrency's genesis block is the very first block mined in the blockchain. The genesis block included the text "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks." This was the headline from the London newspaper The Times. Including this in the genesis block provides two insights. First, it proves that Satoshi Nakamoto had not been mining on the blockchain before releasing it. This is key because Bitcoin uses

¹<https://bitcoin.org/bitcoin.pdf>

²This section borrows information on the history of bitcoin from the public encyclopedia of cryptocurrencies: www.coinmama.com/guide/history-of-bitcoin

Proof of Work, meaning that the blockchain is secured by a race to find a possible answer to a problem only solvable by random guessing. If Satoshi had a head start in mining, he would have the ability to stay ahead of the competition by mining blocks ahead of time and only releasing them at their scheduled times. Second, it provided a commentary about the financial industry at the time. Satoshi designed blockchain and cryptocurrency as an alternative to traditional banking.

On January 9, 2009, six days after mining the genesis block of Bitcoin, Satoshi Nakamoto open-sourced the code for Bitcoin clients, making it possible for anyone to interact with the Bitcoin network (mining and performing transactions) and understand how Bitcoin functioned.

The first Bitcoin transaction was made on January 12, 2009. Satoshi Nakamoto sent to Hal Finney, a programmer and Bitcoin supporter, ten Bitcoins. Until that point, every block was empty (no transactions) and the only activity on the Bitcoin network was mining and earning the associated block rewards.

In August 2013, a judge in Texas was trying a case where the defendant had set up a fake savings and loan service using Bitcoin. The defendant had no intention of returning peoples' Bitcoins to them and attempted to justify this by saying that Bitcoin is just a game and that he was not breaking any laws by doing so. On August 6, 2013, the Texas judge issued a ruling that Bitcoin is in fact a real currency and that the defendant's action was in fact a Ponzi scheme. This was a key milestone for Bitcoin since it was the first time that Bitcoin was recognized in court as a currency and created legal precedent for it to be considered as such into the future.

On October 29, 2013, the first Bitcoin ATM opened near in Vancouver, Canada. This ATM allowed people to buy and sell Bitcoins using a user-friendly interface. The ATM in Vancouver was sponsored by Robocoin and Bitcoiniacs and was one of five planned to open in Canada. The creation of a Bitcoin ATM was an important step toward Bitcoin

becoming a competitor to bank cards and cash. The ability to buy and sell Bitcoin at an ATM can be seen as equivalent to cash deposits and withdrawals at traditional ATMs.

Bitcoin was designed as an alternative to the traditional financial industry (cash, credit cards, etc.) but it has major scalability problems. Bitcoin was designed to have a fixed maximum block size (1 megabyte) and a fixed block rate (ten minutes), meaning that the maximum rate at which Bitcoin can process transactions in the blockchain is limited (up to seven transactions per second). On August 1, 2017 another cryptocurrency called Bitcoin Cash was created from the Bitcoin code. The difference between Bitcoin Cash and Bitcoin is the block size used. Bitcoin Cash used a block size of 8 MB, creating an eightfold increase in the processing capacity of their blockchain compared to Bitcoin.

On August 1, 2017, a group of developers wanting to increase bitcoin's block size limit prepared a code change. The change, called a hard fork, had as a result, the bitcoin ledger called the blockchain and the cryptocurrency to be split in two. At the time of the fork, everyone owning bitcoin units was also in possession of the same number of Bitcoin Cash units. The technical difference between Bitcoin Cash and bitcoin is that Bitcoin Cash permits larger blocks in its blockchain than bitcoin, allowing it to process more transactions per second.

On 15 November 2018 Bitcoin Cash split into two cryptocurrencies, creating Bitcoin SV. The hard-fork chain split of Bitcoin Cash occurred between two rival factions called Bitcoin ABC and Bitcoin SV. On 15 November 2018 Bitcoin Cash ABC traded around \$289 and Bitcoin SV traded at about \$96.50, down from \$425.01 on 14 November for the un-split Bitcoin Cash (noa, 2018).

For the purposes of this study, I consider two points of structural change in the bitcoin market: August 1, 2013 (the date considered as a structural point in efficiency by Urquhart (2016)) and November 15, 2018 (the date of the Bitcoin SV hard fork, due

to its impact on the Bitcoin price).

3 Background on Ethereum

Vitalik Buterin's discontent with the limitations of Bitcoin led to the creation of Ethereum, which has become the second most valuable cryptocurrency in existence at the time of writing.³ Currently, every other cryptocurrency except Bitcoin and Ethereum are only exchangeable with Bitcoin or Ethereum and not directly with traditional currencies or assets. This makes Bitcoin and Ethereum particularly important for the study of the market of cryptocurrencies.

The goal of Bitcoin was to create a decentralized alternative to the existing financial industry. The creator of Ethereum, Vitalik Buterin, saw the potential for using the blockchain technology for other applications and pushed for a scripting language for Bitcoin to make development of applications on the blockchain possible but his proposal was rejected. In late 2013, Buterin proposed the development of a new platform for more generalized scripting and application development. Buterin releases the Ethereum white paper describing the proposed technology in November 2013.

In January 2014, the development of the Ethereum platform started. The Ethereum development group consisted of Vitalik Buterin, Mihai Alisie, Anthony Di Iorio, and Charles Hoskinson. Originally, development of the Ethereum platform was under a Swiss company called Ethereum Switzerland GmbH. The non-profit Ethereum Foundation was founded in June 2014 for the development of the Ethereum cryptocurrency platform. The Ethereum team needed development funding to create the Ethereum Network. Instead of going to venture capitalists, they decided to reach out to the cryptocurrency community in a crowd sale. The Ethereum crowdsale ran in July and Au-

³This section reflects information from the public encyclopedia of cryptocurrencies: <https://www.coinmama.com/guide/history-of-ethereum>

gust 2014 and allowed future users and investors to buy Ether ⁴ (tokens on the future Ethereum blockchain⁵) in exchange for Bitcoin. Since Bitcoin was an established currency at the time, the Ethereum team could trade it in for traditional currency to cover development costs. As a result of the Ethereum crowdsale, 11.9 million Ethereum tokens were purchased (about 13% of the circulating supply), raising approximately 18.4 million USD.

An Ethereum testnet, Olympic, was launched in May 2015. This private network allowed Ethereum developers to work out the kinks and bugs in the Ethereum protocol before public release. Ethereum was designed as a smart contract platform with the ability to write cryptocurrency tokens on the platform. It is not surprising that Ethereum hosted crowdsales as well. The first Ethereum Initial Coin Offering (ICO) was for the cryptocurrency called Augur.

The Augur cryptocurrency's ICO was launched on August 17, 2015 and continued until September 5, 2015. The Ethereum network raised over 5 million US dollars for the development of the Augur cryptocurrency. The purpose of Augur was to decentralize speculation on the financial market and other betting such as sports events, etc. by cutting out the middleman.

Homestead is the name of the first "stable" Ethereum release and occurred on March 14, 2016 on block 1,150,000. The Homestead release happened when the Ethereum blockchain was officially classified by the developers as "safe" and included a number of protocol and networking changes that made future upgrades possible. This and all future upgrades are "hard forks" of the Ethereum network, meaning that the blockchain moving forward from that point is incompatible with the pre-fork version.

The next phase of the Ethereum development road map is called Metropolis and is broken into two distinct stages: Byzantium and Constantinople. The first stage, Byzan-

⁴Interestingly enough, "Ether" in Greek means air.

⁵This allowed users who wanted to support the future Ethereum network to contribute in exchange for a share in the value after launch (similar to buying stock on the stock exchange.)

tium, was implemented as part of Ethereum block 4,370,000, which was created on October 16, 2017. Among other things, major improvements included the introduction of zkSNARKs, delaying the difficulty “time bomb”, transaction status receipts, as well as smart contract upgrades.

Ethereum is a humongous development project and, although it has been active and “stable” for over two years, it is still very much a work in progress. The initial development roadmap included four main stages: Frontier, Homestead, Metropolis, and Serenity. Due to the size of the Metropolis upgrade, it has been broken into two smaller stages: Byzantium and Constantinople. Byzantium is now complete, but Constantinople is still to appear in the future at the time of writing.

For the purposes of this study, I consider two point of structural change in the Ethereum market: March 14, 2016 (the date Homestead, the first stable Ethereum cryptocurrency, was released) and October 16, 2017 (the date Metropolis, the upgraded Ethereum cryptocurrency, was released.)

4 Data and Descriptive Statistics

Many different cryptocurrencies exchanges are available, each with varying popularity and currencies that Bitcoin and Ethereum are denoted in. Therefore we collect data from www.coinmarketcap, which aggregates rates from all available Bitcoin and Ethereum exchanges around the world and provides volume weighted average prices. Therefore this enables a worldwide perspective on the Bitcoin and Ethereum prices, and therefore efficiency of those assets. The data consists of daily closing prices in USD from April 28, 2013 to March 25, 2019 for Bitcoin and from August 7, 2015 to March 25, 2019 for Ethereum.

Figure 1 shows Bitcoin prices and volume over this period and it appears that Bitcoin prices are relatively stable before peaking dramatically in late 2013. However as

[Fry and Cheah \(2016\)](#) show, even the earliest years of this period, the price rises are considerable and therefore we include the full sample period in our analysis. We examine the efficiency of Bitcoin over our full sample period, as well as in three subsamples in order to whether the level of efficient has varied over time. Therefore our full sample period to study the efficiency of Bitcoin is from April 28, 2013 to March 25, 2019, and the three subsample periods are from April 28, 2013 to 31st July 2013, 1st August 2013 to November 14, 2018, and from November 15, 2018 to March 25, 2019. Our full sample period to study the efficiency of Ethereum is from August 7, 2015 to March 25, 2019, and the three subsample periods are from August 7, 2015 to March 13, 2016, March 14, 2016 to October 15, 2017, and from October 16, 2017 to March 25, 2019.

We calculate Bitcoin and Ethereum returns in the following way;

$$R_t = (P_t - P_{t-1})P_{t-1} \quad (1)$$

where R_t is the return of Bitcoin or Ethereum and P_t and P_{t-1} are the closing prices at time t and $t - 1$. Table 1 reports the descriptive statistics of Bitcoin and Ethereum and shows that the mean returns of both Bitcoin and Ethereum are practically zero and over the full sample period with excess kurtosis and negative skewness. It is worth comparing those statistics with those of [Urquhart \(2016\)](#) who find positive daily returns for Bitcoin.

Table 1 presents descriptive statistics for the Bitcoin and Ethereum Markets as well as the Treasury bond yields. Figures 1 through 4 present the time series of returns for Bitcoin and Ethereum. Figures 5 through 7 present the time series of Treasury bond yields, used later in the analysis.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Bitcoin					
Opening Bid	2158	2365.12	3362.00	68.50	19475.80
Closing Bid	2158	2366.72	3361.61	68.43	19497.40
Highest Bid	2158	2433.84	3483.22	74.56	20089.00
Lowest Bid	2158	2288.10	3214.35	65.53	18974.10
Yield	2157	0.00	0.04	-0.23	0.43
Close-Open Spread	2158	1.60	230.77	-2345.60	3633.60
High-Low Spread	2158	145.74	347.11	0.00	4110.40
Ethereum					
Opening Bid	1327	205.61	267.03	0.43	1397.48
Closing Bid	1327	205.64	266.85	0.43	1396.42
Highest Bid	1327	213.55	278.72	0.48	1432.88
Lowest Bid	1327	196.49	253.10	0.42	1290.60
Yield	1326	0.01	0.07	-0.73	0.51
Close-Open Spread	2158	0.03	21.54	-238.94	153.74
High-Low Spread	1327	17.07	33.36	0.02	417.09
Treasury Bond Yields					
3-Month Bond	1556	0.63	0.79	0.00	2.49
10-Year Bond	1556	2.36	0.41	1.37	3.24
10-Year – 3-Month Spread	1556	1.73	0.67	-0.02	2.97

Figure 1: Time Series of Bitcoin log(Price)

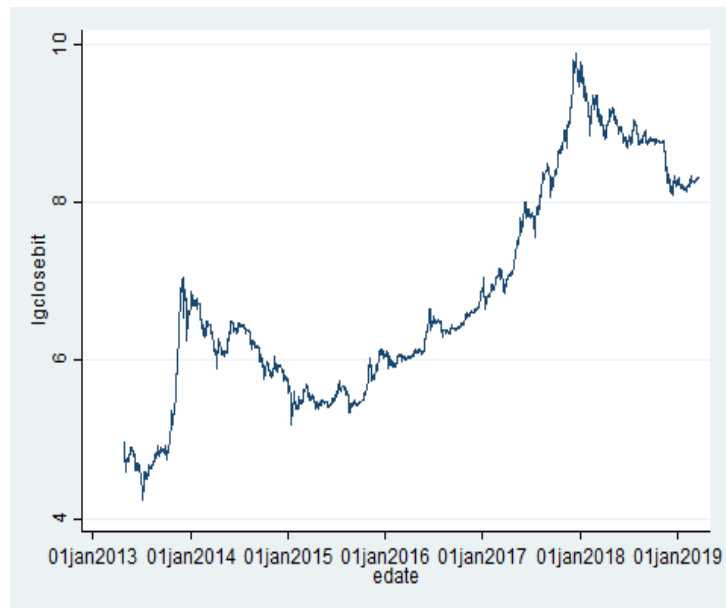


Figure 2: Time Series of Bitcoin Yield

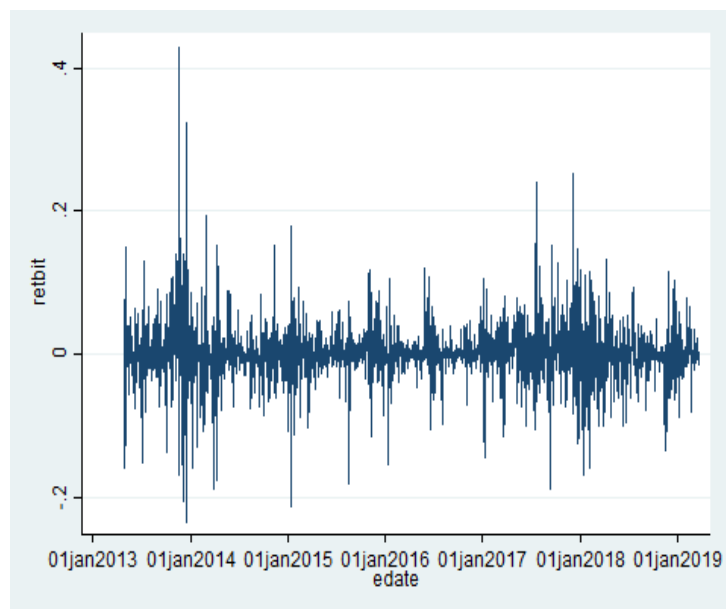


Figure 3: Time Series of Ethereum log(Price)

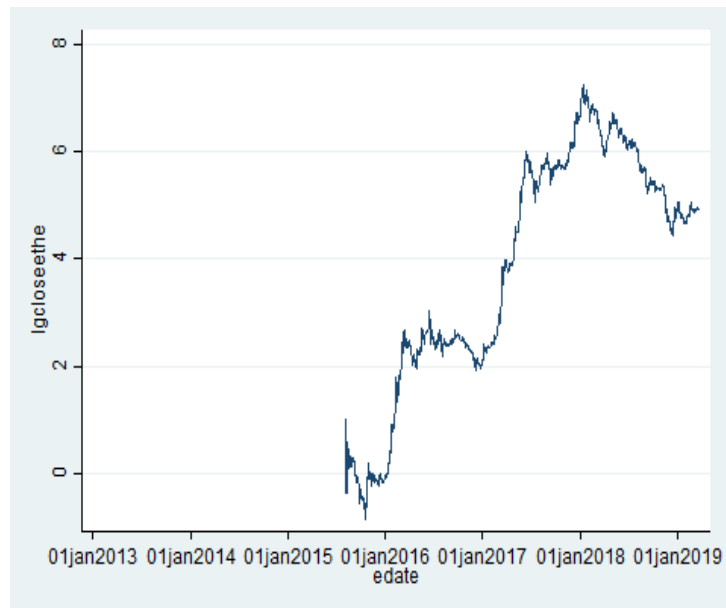


Figure 4: Time Series of Ethereum Yield

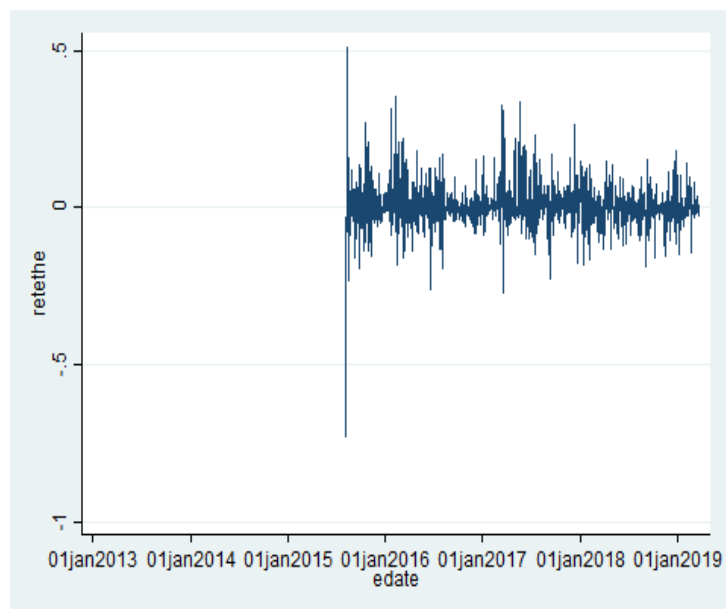


Figure 5: Time Series of 10-Year Bond

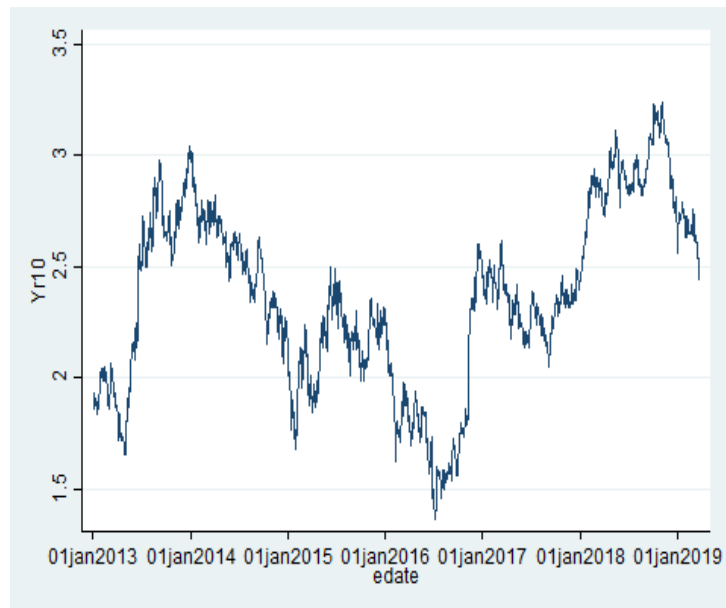


Figure 6: Time Series of 3-Month Bond

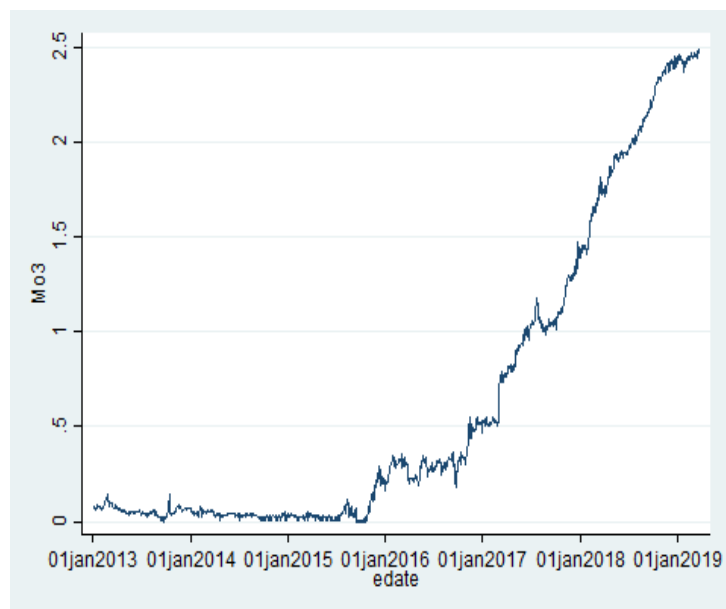
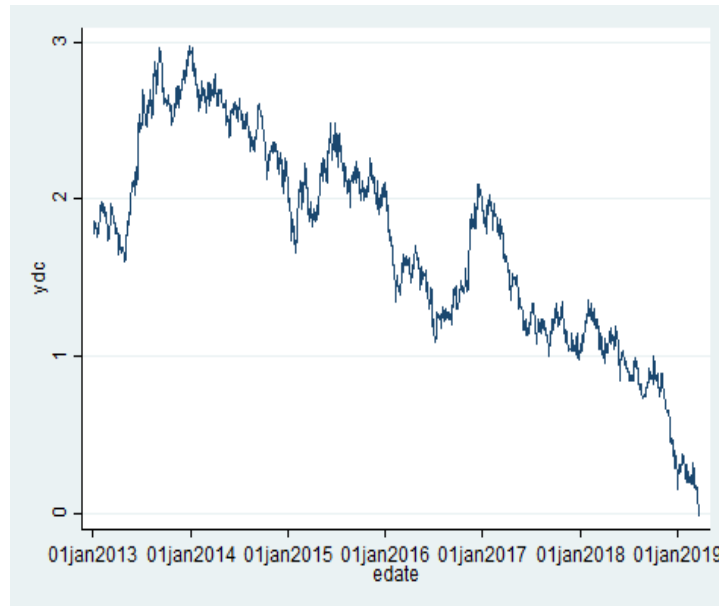


Figure 7: Time Series of Difference between 10-Year and 3-Month Bond Yield



I employ kernel smoothing to compare the distributions of returns for Bitcoin and Ethereum to the standard normal distribution. The kernel density for Bitcoin returns is displayed on figure 8. The kernel density for Ethereum returns is displayed on figure 9. From these plots we can see that returns for both Bitcoin and Ethereum are very similar to a normal distribution yet have a higher peak at the mean value.

Figure 8: Kernel Density of Bitcoin Returns

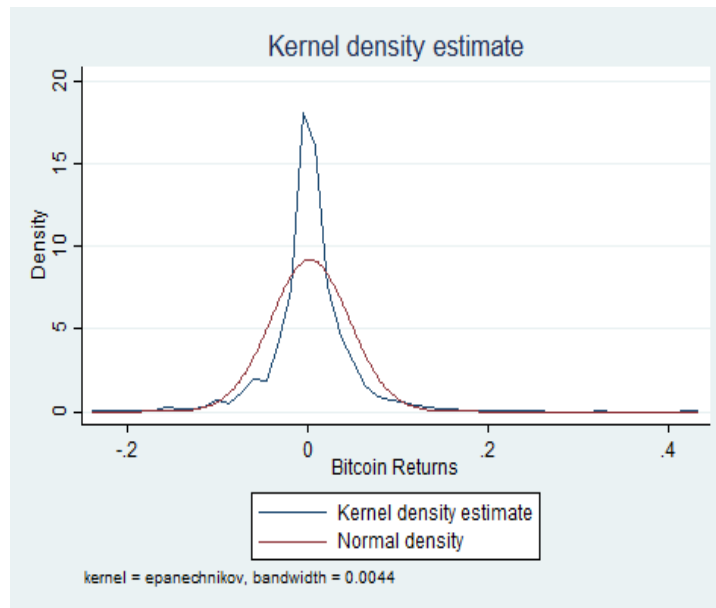
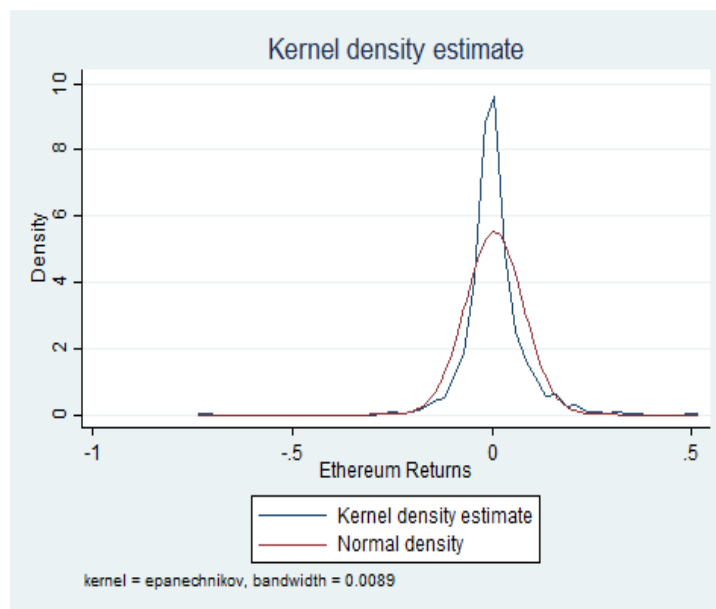


Figure 9: Kernel Density of Ethereum Returns



5 Efficient Market Hypothesis

In this section I investigate whether Bitcoin or Ethereum abide by the weak form of the Efficiency Market Hypothesis. I perform a battery of tests to answer whether past price levels of Bitcoin or Ethereum can predict their respective future values.

The efficient market hypothesis postulates that asset prices reflect all relevant information, and that it is impossible to beat the market or achieve above-average returns on a sustainable basis. There are many critics of the efficient market theory, such as behavioral economists, who believe in inherent market inefficiencies.

The efficient market hypothesis was developed by economist Eugene Fama in his Ph.D. dissertation in the 1960s and essentially says that at any given time, stock prices reflect all available information and trade at exactly their fair value. Thus, it is impossible to consistently choose assets or commodities that will beat the returns of the overall stock market. Basically, the hypothesis implies that the pursuit of market-beating performance is more about chance than it is about researching and selecting the right stocks or the right timing.

There are three flavors, or degrees, of the efficient market hypothesis: weak, semi-strong and strong. The weak form of the efficient market hypothesis assumes that current stock prices reflect all available information, and that past price performance has no relationship with the future. In other words, this form of the efficient market hypothesis claims that using technical analysis to achieve exceptional returns is impossible.

The semi-strong form claims that asset prices have factored in all available public information (i.e., not only past prices.) Therefore, it's impossible to use fundamental analysis to choose stocks that will beat the market's returns.

Finally, the strong form of the efficient market hypothesis postulates that all information – public as well as private – is incorporated into current asset prices. This form

of the efficient market hypothesis essentially describes a perfect market and isn't possible when there are insider trading restrictions.

Perhaps the biggest piece of evidence to refute the efficient market hypothesis in the real world is the existence of market bubbles and crashes. For instance, if the assumptions of the efficient market hypothesis were correct, the housing bubble and stock market crash of 2008 wouldn't have occurred. The same argument can be made about the tech bubble of the late 1990s, when many tech companies were trading for sky-high valuations before crashing.

Additionally, there are investors who have consistently beaten the market. As a famous example, Warren Buffett has been a major critic of the efficient market hypothesis, who using his value investing approach and trying to identify a safety margin in stocks has achieved returns that have been far superior to those of the market (and he has done it steadily over a 50-year period of time.)

Behavioral economists are also highly critical of the efficient market hypothesis. In a nutshell, behavioral economists maintain that investors are susceptible to certain biases, such as the belief that past performance is indicative of the future. These biases can lead to mispricings of assets, according to proponents.

The efficient market hypothesis together with rational expectations suggest that the returns to cryptocurrencies should follow a random walk or a random walk with a drift, so that their differences (between time t and time $t-1$) are unpredictable (stationary). The random walk process is defined in model 2 with $\phi = 1$. When $\phi = 1$, we say the times series has a unit root.

$$Y_t = \mu + \phi Y_{t-1} + \epsilon_t \quad (2)$$

where Y_t is the return of an asset of interest (Bitcoin or Ethereum) at time t . Param-

eter μ represents the drift of the time series. If $\phi = 0$, the series is called a white noise or stationary process.

5.1 Autocorrelations and Partial Autocorrelations

I plot the autocorrelation and partial autocorrelation function for Bitcoin and Ethereum. The autocorrelation function measures the similarity of returns as a function of the time separation between them. The partial autocorrelation function is an extension of the autocorrelation function, where the dependence on the intermediate elements is excluded.

The plot the autocorrelation function (ACF) plot and the partial autocorrelation function (PACF) plot are displayed in figures 10 through 13. It can be clearly seen from these plots that only a few of the lags of the variables are statistically significant (they are outside the confidence interval around zero.) The statistically significant lags on the ACF plot, those that break through the confidence interval, may indicate the existence of an autoregressive process at those lags while the PACF spikes indicate lags where a moving average may be present. The autocorrelation or partial autocorrelation of most of the lags of returns of either Bitcoin or Ethereum remain within the confidence interval, without a clear pattern for those that break through the support line.

Figure 10: Auto-correlation of Bitcoin Yield

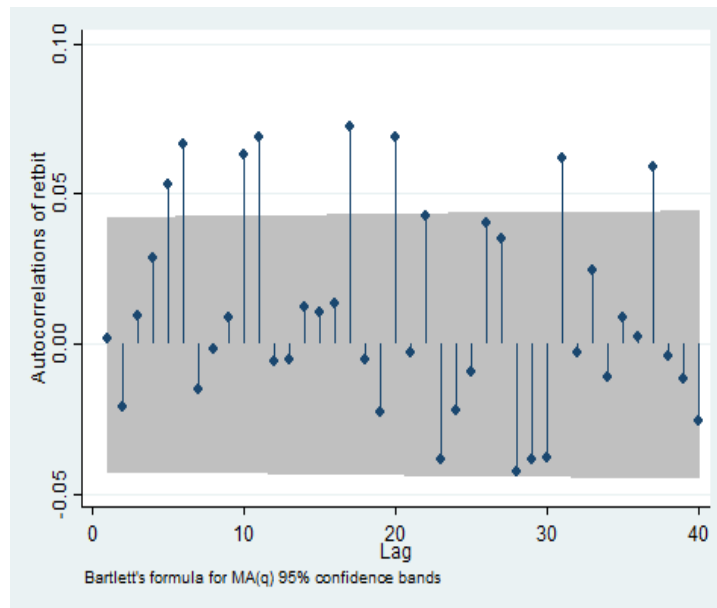


Figure 11: Partial Auto-correlation of Bitcoin Yield

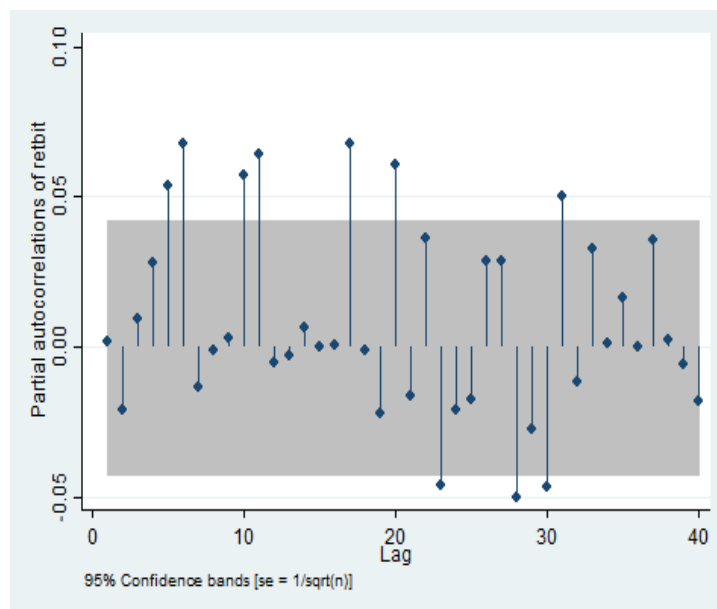


Figure 12: Auto-correlation of Ethereum Yield

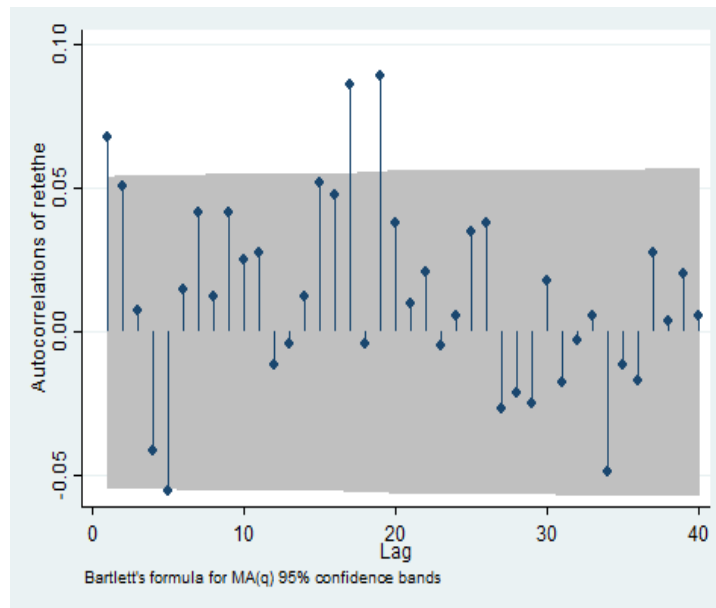
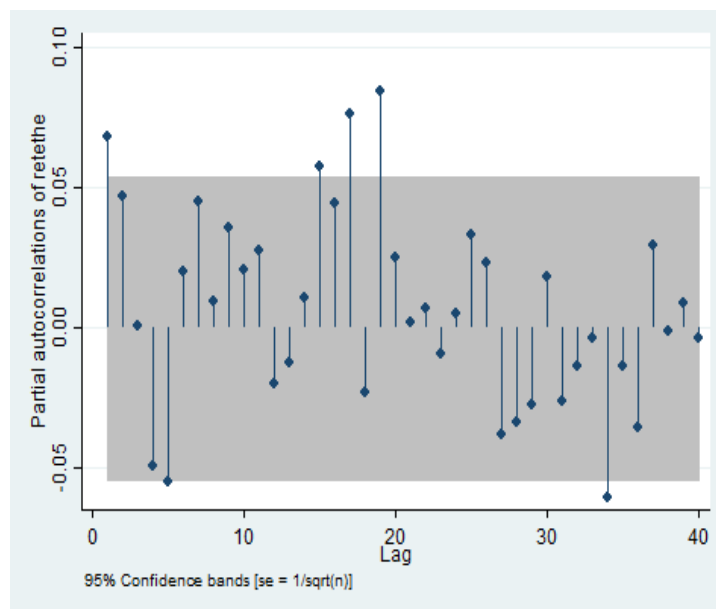


Figure 13: Partial Auto-correlation of Ethereum Yield



5.2 Testable Hypothesis

In this section I am testing the weak form efficiency of the efficient market hypothesis, the possibility that returns can be predicted from past returns. The hypothesis that returns cannot be predicted from past returns can be stated as: $E(R_t | R_{t-1}, R_{t-2}, \dots) = E(R_t)$ Where R_t is the return at time t .

5.3 Statistical Tests

In an efficient market, future prices are not foreseeable and variations are random and due to the random nature of unpredictable events and thus prices follow a random walk. To investigate whether Bitcoin and Ethereum are efficient, I employ a battery of highly powerful tests for randomness in order to avoid spurious results and to capture all the dynamics of Bitcoin and Ethereum.

I present results for the daily returns to Bitcoin and Ethereum as well as for the difference (spread) of those returns relative to the 3-month and the 10-year treasury bills. The idea is to test whether any predictability of future returns (of Bitcoin or Ethereum) by past returns goes away when controlling for the trend in risk in the overall economy captured by the 3-month treasury bill rate in the short-term and the 10-year treasury bill rate in the long-term.

Firstly, I test the autocorrelation of Bitcoin and Ethereum returns which are assessed via the Ljung-Box ([Ljung and Box, 1978](#)) test that has the null hypothesis of no autocorrelation.

Secondly, I employ the runs test ([Wald and Wolfowitz, 1940](#)) to determine whether returns of Bitcoin and Ethereum are serially independent, which has independence as the null hypothesis.

Thirdly, I employ the Bera-Jarque test [Lo and MacKinlay \(1988\)](#), which under the null hypothesis, the returns process follows a normal distribution. Lastly, I use an Aug-

mented Dickey-Fuller test to test the null hypothesis of a unit root in the time series of returns of Bitcoin and Ethereum. Having a unit root in the time series means that the future returns can be predicted by past returns.

5.3.1 Tests of White Noise

The portmanteau test of white noise is first presented graphically in figures 14 and 15. The figures support the claim that the returns of Bitcoin and Ethereum follow a white noise process, and thus are not foreseeable using past price information. The augmented Dickey-Fuller test results are summarized in tables 10 for Bitcoin and 11 for Ethereum. I present results for varying numbers of lags included in the autoregressive model of returns; 1, 3, 6, 9, and 12 lags are explored. The augmented Dickey-Fuller test tests the null hypothesis that all the coefficients corresponding to the influences of all lagged values of dependent variable are simultaneously zero. Rejecting the null hypothesis of the augmented Dickey-Fuller test suggest that returns to Bitcoin and Ethereum contain no unit root and thus the time series of returns follows a process closer to a stationary one rather than a random walk. The results presented correspond to the model without a drift, even though the results are robust to including a drift in the model.

Figure 14: Tests of White Noise of Bitcoin Yield

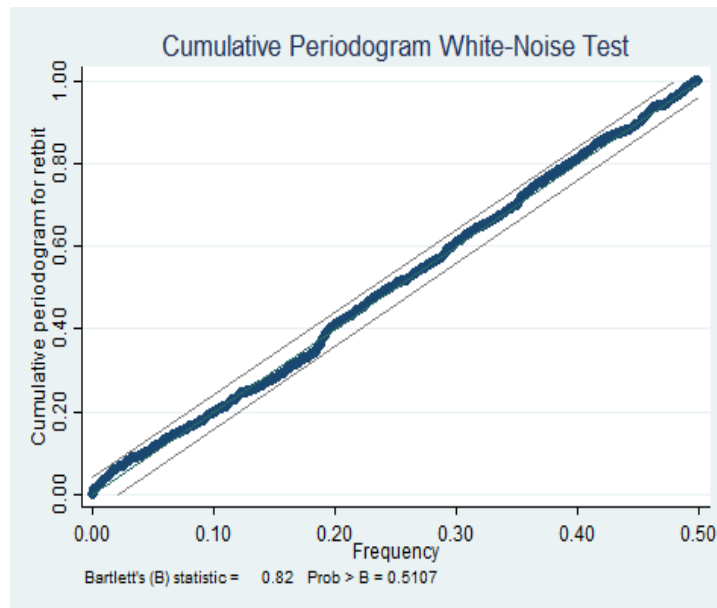
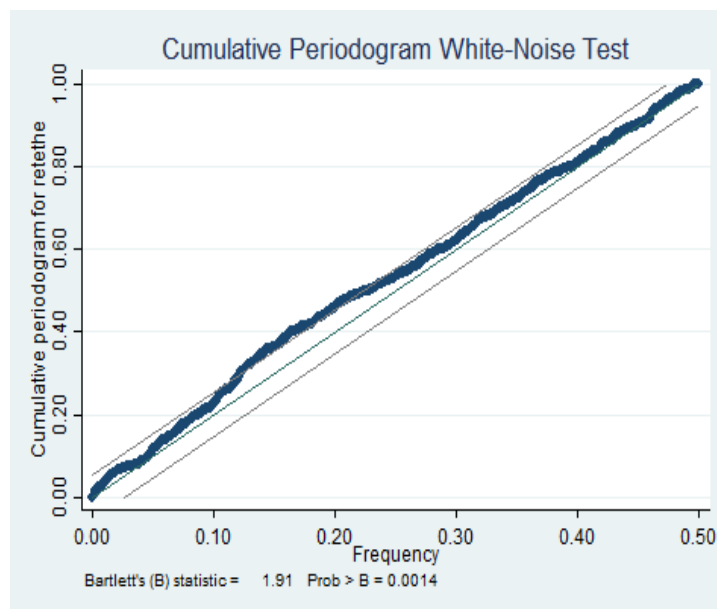


Figure 15: Tests of White Noise of Ethereum Yield



5.3.2 Ljung-Box Test

Table 2: Ljung-Box Test of White Noise for Bitcoin

Ljung-Box Test of White Noise P Values			
Period	Return	Spread Over 3-Month Bill	Spread Over 10-Year Bill
28apr2013-25mar2019	0.00	0.00	0.00
28-apr2013-31jul2013	0.82	0.97	0.00
01aug2013-14nov2018	0.00	0.00	0.00
15nov2018-25mar2019	0.55	0.79	0.00

Table 3: Ljung-Box Test of White Noise for Ethereum

Ljung-Box Test of White Noise P Values			
Period	Return	Spread Over 3-Month Bill	Spread Over 10-Year Bill
07aug2015-25mar2019	0.01	0.00	0.00
07aug2015-13mar2016	0.47	0.00	0.00
14mar2016-15oct2017	0.94	0.00	0.00
16oct2017-25mar2019	0.13	0.00	0.00

5.3.3 Runs Test

Table 4: Runs Test for Bitcoin

Runs Test P Values			
Period	Return	Spread Over 3-Month Bill	Spread Over 10-Year Bill
28apr2013-25mar2019	0.25	0.00	0.00
28-apr2013-31jul2013	1.00	0.32	0.00
01aug2013-14nov2018	0.52	0.00	0.00
15nov2018-25mar2019	0.03	0.03	0.00

Table 5: Runs Test for Ethereum

Period	Runs Test P Values		
	Return	Spread Over 3-Month Bill	Spread Over 10-Year Bill
07aug2015-25mar2019	0.55	0.00	0.00
07aug2015-13mar2016	0.38	0.00	0.00
14mar2016-15oct2017	0.34	0.00	0.00
16oct2017-25mar2019	0.34	0.00	0.00

5.3.4 Bera-Jarque Test

Table 6: Bera-Jarque Test of Normality for Bitcoin

Period	Bera-Jarque Test of Normality P Values		
	Return	Spread Over 3-Month Bill	Spread Over 10-Year Bill
28apr2013-25mar2019	0.00	0.00	0.00
28-apr2013-31jul2013	0.00	0.01	0.00
01aug2013-14nov2018	0.00	0.00	0.00
15nov2018-25mar2019	0.00	0.00	0.01

Table 7: Bera-Jarque Test of Normality for Ethereum

Period	Bera-Jarque Test of Normality P Values		
	Return	Spread Over 3-Month Bill	Spread Over 10-Year Bill
07aug2015-25mar2019	0.00	0.00	0.00
07aug2015-13mar2016	0.00	0.00	0.00
14mar2016-15oct2017	0.00	0.00	0.00
16oct2017-25mar2019	0.00	0.00	0.00

5.3.5 Augmented Dickey-Fuller Test

Table 8: Augmented Dickey-Fuller Test for Bitcoin

Augmented Dickey-Fuller Test MacKinnon P Values: 1 Lag			
Period	Return	Spread Over 3-Month Bill	Spread Over 10-Year Bill
28apr2013-25mar2019	0.00	0.30	0.02
28-apr2013-31jul2013	0.00	0.00	0.60
01aug2013-14nov2018	0.00	0.59	0.12
15nov2018-25mar2019	0.00	0.00	0.07

Table 9: Augmented Dickey-Fuller Test for Ethereum

Augmented Dickey-Fuller Test MacKinnon P values: 1 Lag			
Period	Return	Spread Over 3-Month Bill	Spread Over 10-Year Bill
07aug2015-25mar2019	0.00	0.16	0.00
07aug2015-13mar2016	0.00	0.00	0.00
14mar2016-15oct2017	0.00	0.14	0.13
16oct2017-25mar2019	0.00	0.13	0.00

Table 10: Augmented Dickey-Fuller Test for Bitcoin: Multiple Lags

Augmented Dickey-Fuller Test MacKinnon P-values: Varying Lags

Lags:	3 Lags	6 Lags	9 Lags	12 Lags
Period	Dependent Variable: Bitcoin Return			
28apr2013-25mar2019	0.00	0.00	0.00	0.00
28-apr2013-31jul2013	0.00	0.03	0.00	0.12
01aug2013-14nov2018	0.00	0.00	0.00	0.00
15nov2018-25mar2019	0.00	0.00	0.02	0.05

Table 11: Augmented Dickey-Fuller Test for Ethereum: Multiple Lags

Augmented Dickey-Fuller Test MacKinnon P-values: Varying Lags				
Lags:	3 Lags	6 Lags	9 Lags	12 Lags
Period	Dependent Variable: Ethereum Return			
07aug2015-25mar2019	0.00	0.00	0.00	0.00
07aug2015-13mar2016	0.00	0.00	0.00	0.00
14mar2016-15oct2017	0.00	0.00	0.00	0.00
16oct2017-25mar2019	0.00	0.00	0.00	0.00

5.4 Results

Overall, I find evidence that the returns to Bitcoin and Ethereum follow a random walk process. The results do not differ by subsample period for either Bitcoin or Ethereum. The Ljung–Box test reject its null hypotheses in the full sample, indicating autocorrelation and that Bitcoin is indeed efficient. The Ljung–Box test does not reject its null hypothesis in the second subsample period for Bitcoin and either subsample period of Ethereum. The other tests all indicate that Bitcoin and Ethereum are efficient (weak-form efficiency.) The results for the difference of the Bitcoin yield and the Ethereum yield over the 10-year Tbill show efficiency of that time series, suggesting that any predictability of profits over the safe assets of 10-year or the 3-month US bonds is not plausible. The augmented Dickey-Fuller tests reject the null hypothesis that all the coefficients corresponding to lagged levels of the dependent variable are simultaneously zero for the entire period in the dataset for both Bitcoin and Ethereum at varying numbers of lags included in the model. Our results suggest that Bitcoin and Ethereum follow a random walk process over our full sample period, as well as in the first and third subsample periods.

6 Is demand for cryptocurrencies pro-cyclical?

In this section, I investigate whether the cryptocurrencies behave like a hedging position for the traditional economy. To test this empirically, I study the association between the returns to cryptocurrencies and a proxy for the uncertainty in the global economy, the US Yield Curve. If indeed cryptocurrencies are negatively associated with the Yield Curve, it would mean that the demand for cryptocurrencies is pro-cyclical and cryptocurrencies can be used for hedging against the traditional economy.

A yield curve is a curve or a line that plots the interest rates, at a set point in time, of bonds having equal credit quality (like treasury bonds) but differing maturity dates. The most commonly reported yield curve compares the three-month, two-year, five-year, 10-year and 30-year U.S. Treasury debt. This yield curve is used as a benchmark for other debt in the market, such as mortgage rates or bank lending rates, and it is often used to predict changes in economic output and growth. The US Yield Curve in this study is measured as the difference between the 10-year and 3-month Treasury bills.

6.1 Empirical Investigation

I model the association between daily returns of Bitcoin and Ethereum and the yield curve in a straightforward manner.

$$Y_t = \alpha + \beta YDC_t + \epsilon_t \quad (3)$$

Where Y_t is the daily return of a cryptocurrency at time t , and YDC_t is the daily US Yield Curve measure at time t . The cryptocurrencies can be seen as alternatives to traditional currencies and assets in the economy. Thus, one may think that investors

may use cryptocurrencies to hedge against the traditional economy. To test this hypothesis, I investigate the association of the price change (day-to-day rate of change) and a measure of performance or trust in the traditional economy. I use the difference between the yields of the 10-year and the 3-month Treasury bills to proxy the trust investors have on the traditional economy. The difference in the yields of relatively safe assets like the treasury bills of different maturity is viewed by financial practitioners as an approximation of the relative uncertainty about the current state of the economy compared to the uncertainty about the future state of the economy.

In the absence of a crisis or a financial turmoil, the near future should be less uncertain than the distant future and thus the yield of the 3-month T-bill should be lower than the yield of the 10-year treasury bond. If the investors foresee a crisis in the near future the direction of the difference in the yields of treasury bonds of different maturity flips and the distant future is associated with lower yield than the near future as there is more uncertainty about the near future than the distant future.

6.2 Results

Tables 12 and 13 show the OLS estimates of specification 3. The results show no evidence of significant association between the Yield Curve and the returns to either Bitcoin or Ethereum. These findings suggest that the market for cryptocurrencies may attract investors for reasons that are not associated with the uncertainty in the traditional economy. In other words, we find no evidence to support the claim that Bitcoin or Ethereum are used as hedging vehicles against assets that reflect the performance of the traditional economy. In this economy, the Yield Curve of the US economy is assumed to reflect the uncertainty of investors in the global economy given the size of the American economy and the traditional role of the US Dollar as a store of value in eras of global financial or political turmoil.

Table 12: The Association between the Yield Curve and Returns to Bitcoin

	(1)	(2)	(3)	(4)
Yield Curve	0.001 (0.002)	0.001 (0.002)	0.004 (0.005)	0.006 (0.005)
Observations	1,476	1,476	1,476	1,476
R-squared	0.000	0.000	0.000	0.001
Risk-free control	NO	YES	NO	YES
Linear Trend	NO	NO	YES	YES

Note: The dependent variable in each specification is daily returns. Standard errors reported in parentheses. The yield curve is defined as the spread between the interest rate of the 10-bill and the 3-month T-bills. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 13: The Association between the Yield Curve and Returns to Ethereum

	(1)	(2)	(3)	(4)
Yield Curve	0.009* (0.005)	0.004 (0.006)	-0.008 (0.010)	0.002 (0.018)
Observations	904	904	904	904
R-squared	0.004	0.009	0.008	0.009
Risk-free control	NO	YES	NO	YES
Linear Trend	NO	NO	YES	YES

Note: The dependent variable in each specification is daily returns. Standard errors reported in parentheses. The yield curve is defined as the spread between the interest rate of the 10-bill and the 3-month T-bills. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

7 Can Google searches predict the Cryptocurrencies' market?

One may think that investors in cryptocurrencies may not be people who savvy in the financial markets. Moreover, new investors in cryptocurrencies may potentially be people who had never heard about Bitcoin or Ethereum before their popularity rose and public and the media became interested in cryptocurrencies. In this section I empiri-

cally investigate whether the market outcomes of cryptocurrencies (price and volume) are driven by popularity. If a market is driven by herding behavior like fashion or popularity, we say that the market is driven by noise traders, as opposed to smart money, investors who are better informed about the fundamental value of the asset they are investing in.

To proxy cryptocurrencies' popularity I use a Google searches index for the entire period covered in the data (April 2013-March 2018). The Google searches data reflect a monthly index taking values between 0 and 100 ⁶. The data on Google searches for terms like "ethereum" or "cryptocurrencies" were rather poor. Therefore, for the analysis of this section I use the index of Google searches for the term "bitcoin" to proxy public popularity of the cryptocurrencies market.

7.1 Empirical Methodology

I model the effect of Google searches on the market outcomes (price and volume) of Bitcoin and Ethereum in a straightforward manner. I start off with a simple specification without any lags, estimated at the month level:

$$Y_t = \alpha + \beta G_t + \epsilon_t \quad (4)$$

Where Y_t is the closing price or volume of a cryptocurrency in month t and G_t is the Google Searches index at month t . I gradually augment specification 3 with additional lags to investigate dynamic effects (longer memory) of cryptocurrency popularity (proxied by Google searches of the term "Bitcoin") on the market outcomes to further understand whether the cryptocurrencies market is driven primarily by noise traders (traders without knowledge of the fundamental characteristics of the asset

⁶The mean value of Google searches for the term "bitcoin" is 8.207 with a standard deviation of 13.662

they are investing in) as opposed to smart money (informed investors whose behavior is not driven by crowd behavior and thus less likely to correlate with Google searches.)

7.2 Results

The results in this subsection show that the Google searches of the term "Bitcoin" can indeed predict not only concurrent but also future market outcomes (price and volume) for both Bitcoin and Ethereum, although the association is stronger (more than an order of magnitude) for the Bitcoin market outcomes. Tables 14 through 17 show OLS estimates of specification 4 for Bitcoin, augmented with additional lags of the key independent variable (Google searches index). Tables 18 through 21 show OLS estimates for specification 4 for Ethereum, along with the model modifications to include additional lags and compare the parameters of interest.

Table 14: The Association between the Google Searches and Bitcoin: No Lags

VARIABLES	(1)	(2)	(3)	(4)
	Mean Closing Price	Mean Log(Closing Price)	Mean Daily Return	Mean Log(Daily Volume)
bitcoin: (Worldwide)	196.227*** (26.878)	0.064*** (0.018)	0.000* (0.000)	0.096*** (0.028)
Observations	72	72	72	64
R-squared	0.729	0.443	0.101	0.390
Linear Trend	YES	YES	YES	YES

Note: The dependent variable in each specification is shown at the column header. Standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 15: The Association between the Google Searches and Bitcoin: 3 Lags

VARIABLES	(1)	(2)	(3)	(4)
	Mean Closing Price	Mean Log(Closing Price)	Mean Daily Return	Mean Log(Daily Volume)
bitcoin: (Worldwide)	189.266*** (24.689)	0.058*** (0.016)	0.000** (0.000)	0.091*** (0.024)
bitcoin: (Worldwide) = L1,	41.748** (20.585)	0.032*** (0.011)	-0.000** (0.000)	0.061*** (0.018)
bitcoin: (Worldwide) = L2,	-8.575 (20.476)	-0.075*** (0.017)	0.000 (0.000)	0.095* (0.056)
bitcoin: (Worldwide) = L3,	-52.212*** (14.912)	-0.016 (0.016)	0.000 (0.000)	-0.067*** (0.016)
Observations	71	71	71	63
R-squared	0.788	0.635	0.153	0.639
Linear Trend	YES	YES	YES	YES

Note: The dependent variable in each specification is shown at the column header. Standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 16: The Association between the Google Searches and Bitcoin: 6 Lags

VARIABLES	(1)	(2)	(3)	(4)
	Mean Closing Price	Mean Log(Closing Price)	Mean Daily Return	Mean Log(Daily Volume)
bitcoin: (Worldwide)	172.448*** (16.918)	0.048*** (0.012)	0.000** (0.000)	0.067*** (0.015)
bitcoin: (Worldwide) = L1,	25.330 (16.167)	0.027*** (0.010)	-0.000** (0.000)	0.044*** (0.013)
bitcoin: (Worldwide) = L2,	-50.473 (36.434)	-0.108*** (0.027)	-0.000 (0.000)	0.150** (0.069)
bitcoin: (Worldwide) = L3,	-83.847*** (26.041)	-0.028 (0.024)	0.000 (0.000)	-0.104*** (0.023)
bitcoin: (Worldwide) = L4,	-58.065*** (16.494)	-0.038*** (0.012)	-0.000*** (0.000)	-0.062*** (0.019)
bitcoin: (Worldwide) = L5,	-49.587*** (15.016)	-0.033*** (0.012)	0.000 (0.000)	-0.083*** (0.019)
bitcoin: (Worldwide) = L6,	-66.057*** (23.662)	-0.014 (0.009)	0.000 (0.000)	-0.039** (0.019)
Observations	68	68	68	60
R-squared	0.854	0.753	0.200	0.832
Linear Trend	YES	YES	YES	YES

Note: The dependent variable in each specification is shown at the column header. Standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 17: The Association between the Google Searches and Bitcoin: 12 Lags

VARIABLES	(1) Mean Closing Price	(2) Mean Log(Closing Price)	(3) Mean Daily Return	(4) Mean Log(Daily Volume)
bitcoin: (Worldwide)	146.674*** (11.269)	0.031*** (0.010)	0.000* (0.000)	0.040*** (0.010)
bitcoin: (Worldwide) = L1,	-9.493 (29.865)	0.003 (0.013)	-0.000 (0.000)	0.009 (0.014)
bitcoin: (Worldwide) = L2,	-30.885 (39.018)	-0.120*** (0.031)	-0.000 (0.000)	0.077 (0.067)
bitcoin: (Worldwide) = L3,	-51.674*** (16.910)	-0.007 (0.024)	-0.000 (0.000)	-0.079*** (0.027)
bitcoin: (Worldwide) = L4,	-28.723* (16.072)	-0.025** (0.011)	-0.001** (0.000)	-0.024 (0.017)
bitcoin: (Worldwide) = L5,	-49.836*** (18.291)	-0.027 (0.016)	0.000 (0.000)	-0.091*** (0.023)
bitcoin: (Worldwide) = L6,	-51.666*** (24.445)	-0.010 (0.009)	0.000 (0.000)	-0.032* (0.016)
bitcoin: (Worldwide) = L7,	-8.558 (20.117)	0.016 (0.013)	0.000 (0.000)	0.010 (0.016)
bitcoin: (Worldwide) = L8,	82.458** (40.814)	0.039** (0.016)	-0.000 (0.000)	0.049** (0.021)
bitcoin: (Worldwide) = L9,	14.619 (27.633)	0.027* (0.014)	0.000* (0.000)	0.060*** (0.021)
bitcoin: (Worldwide) = L10,	-58.339 (37.592)	-0.026 (0.029)	0.001 (0.001)	-0.057 (0.036)
bitcoin: (Worldwide) = L11,	-42.972** (21.324)	-0.036** (0.015)	0.000** (0.000)	-0.093*** (0.023)
bitcoin: (Worldwide) = L12,	-33.197* (17.472)	-0.009 (0.012)	0.000 (0.000)	-0.031* (0.018)
Observations	64	64	64	56
R-squared	0.881	0.825	0.252	0.909
Linear Trend	YES	YES	YES	YES

Note: The dependent variable in each specification is shown at the column header. Standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 18: The Association between the Google Searches and Ethereum: No Lags

VARIABLES	(1)	(2)	(3)	(4)
	Mean Closing Price	Mean Log(Closing Price)	Mean Daily Return	Mean Log(Daily Volume)
bitcoin: (Worldwide)	11.259*** (3.237)	0.077*** (0.025)	0.000 (0.000)	0.092*** (0.029)
Observations	44	44	44	44
R-squared	0.582	0.374	0.051	0.312
Linear Trend	YES	YES	YES	YES

Note: The dependent variable in each specification is shown at the column header. Standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 19: The Association between the Google Searches and Ethereum: 3 Lags

VARIABLES	(1)	(2)	(3)	(4)
	Mean Closing Price	Mean Log(Closing Price)	Mean Daily Return	Mean Log(Daily Volume)
bitcoin: (Worldwide)	10.719*** (3.194)	0.068*** (0.021)	0.000 (0.000)	0.083*** (0.023)
bitcoin: (Worldwide) = L1,	0.955 (0.870)	0.043*** (0.014)	-0.000 (0.000)	0.085*** (0.022)
bitcoin: (Worldwide) = L2,	-17.330* (9.686)	-0.344*** (0.099)	0.000 (0.001)	-0.377*** (0.124)
bitcoin: (Worldwide) = L3,	-16.813* (8.698)	-0.042 (0.096)	-0.001 (0.001)	-0.058 (0.121)
Observations	44	44	44	44
R-squared	0.617	0.564	0.100	0.608
Linear Trend	YES	YES	YES	YES

Note: The dependent variable in each specification is shown at the column header. Standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 20: The Association between the Google Searches and Ethereum: 6 Lags

VARIABLES	(1)	(2)	(3)	(4)
	Mean Closing Price	Mean Log(Closing Price)	Mean Daily Return	Mean Log(Daily Volume)
bitcoin: (Worldwide)	9.768*** (3.191)	0.060*** (0.016)	-0.000 (0.000)	0.072*** (0.016)
bitcoin: (Worldwide) = L1,	-1.871 (1.136)	0.005 (0.008)	0.000 (0.000)	0.039*** (0.014)
bitcoin: (Worldwide) = L2,	11.672 (12.279)	0.158 (0.129)	-0.002 (0.002)	0.258 (0.157)
bitcoin: (Worldwide) = L3,	-5.259 (14.842)	-0.064 (0.105)	-0.002 (0.001)	-0.092 (0.153)
bitcoin: (Worldwide) = L4,	-7.867 (7.358)	-0.226*** (0.046)	0.002 (0.002)	-0.282*** (0.050)
bitcoin: (Worldwide) = L5,	-5.788 (4.590)	-0.135*** (0.028)	-0.000 (0.001)	-0.174*** (0.031)
bitcoin: (Worldwide) = L6,	-7.815*** (2.523)	-0.069*** (0.016)	0.001*** (0.000)	-0.082*** (0.022)
Observations	42	42	42	42
R-squared	0.715	0.858	0.268	0.879
Linear Trend	YES	YES	YES	YES

Note: The dependent variable in each specification is shown at the column header. Standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 21: The Association between the Google Searches and Ethereum: 12 Lags

VARIABLES	(1) Mean Closing Price	(2) Mean Log(Closing Price)	(3) Mean Daily Return	(4) Mean Log(Daily Volume)
bitcoin: (Worldwide)	7.620*** (1.994)	0.040** (0.014)	0.000 (0.000)	0.050*** (0.016)
bitcoin: (Worldwide) = L1,	-3.144 (2.898)	-0.011 (0.015)	0.000 (0.000)	0.012 (0.016)
bitcoin: (Worldwide) = L2,	29.159 (20.226)	0.147 (0.109)	-0.002 (0.003)	0.209 (0.126)
bitcoin: (Worldwide) = L3,	2.638 (9.704)	-0.041 (0.083)	-0.003 (0.002)	-0.114 (0.094)
bitcoin: (Worldwide) = L4,	4.747 (16.508)	-0.047 (0.082)	0.001 (0.002)	-0.118 (0.082)
bitcoin: (Worldwide) = L5,	-11.303 (8.529)	-0.113* (0.055)	-0.000 (0.001)	-0.157** (0.063)
bitcoin: (Worldwide) = L6,	-8.358* (4.449)	-0.075*** (0.025)	0.001* (0.001)	-0.105*** (0.028)
bitcoin: (Worldwide) = L7,	-3.998 (2.512)	-0.009 (0.026)	0.001 (0.001)	-0.018 (0.030)
bitcoin: (Worldwide) = L9,	5.023 (5.759)	0.027 (0.028)	-0.000 (0.000)	0.029 (0.028)
bitcoin: (Worldwide) = L9,	-4.662 (5.263)	0.003 (0.027)	0.000 (0.000)	0.023 (0.030)
bitcoin: (Worldwide) = L10,	5.427 (23.122)	0.053 (0.163)	0.001 (0.003)	0.237 (0.191)
bitcoin: (Worldwide) = L11,	-13.298 (14.964)	-0.184* (0.091)	0.001 (0.002)	-0.143 (0.094)
bitcoin: (Worldwide) = L12,	1.037 (9.401)	-0.070 (0.056)	0.001 (0.001)	-0.084 (0.066)
Observations	40	40	40	40
R-squared	0.832	0.926	0.452	0.947
Linear Trend	YES	YES	YES	YES

Note: The dependent variable in each specification is shown at the column header. Standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

8 Conclusion

This study shows that the Bitcoin and the Ethereum markets are weakly efficient over the full sample period. My study updates the findings of earlier literature ([Urquhart, 2016](#)) that suggested Bitcoin was inefficient, even though he found traces of increased efficiency in 2016. One might believe that because both Bitcoin and Ethereum are relatively new investment assets and still in their infancy, they would be similar to an emerging market and therefore inefficient. This study shows that the Bitcoin and Ethereum markets have matured getting closer to weak-form efficiency in the sense that past returns (difference in price levels over time) have little predictability on future returns. Future research could investigate other forms of efficiency in the Bitcoin and the Ethereum Markets.

This study also investigated the degree to which Bitcoin and Ethereum can be viewed as hedging vehicles against the traditional economy and has found no evidence of that hypothesis. Lastly, I have investigated whether the market for Bitcoin and the market for Ethereum are driven by noise traders. I have found that indeed the popularity of Bitcoin among the public, proxied by Google searches of the term "Bitcoin" has strong predictive power over the price and volume of transactions of both Bitcoin and Ethereum.

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