Lund University

Is Bitcoin a Safe Haven?

Bachelor Thesis

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Abstract

The objective of this bachelor thesis is to assess the safe haven property of Bitcoin by conducting an augmented Dickey-Fuller test and Engle and Granger cointegration test with price data from the COVID-19 crash. The analysis revealed a cointegration relationship between Bitcoin and the S&P 500, indicating a long-run equilibrium between the two and thus providing evidence against the safe haven property. Using the same approach on data from the period 2016-01-04 to 2019-09-30, no evidence of cointegration was found. The results are discussed in relation to previous research and the efficient market hypothesis.

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1 Introduction

Bitcoin is the world's most valuable cryptocurrency and during the last couple of years it has grown too big to be ignored by traditional finance. During its peak in November 2021, Bitcoin had a market capitalization of around $1.3 trillion, which is almost as large as the current market cap of silver, $1.33 trillion (companiesmarketcap.com 2022, see appendix 7.1 for calculation). Such growth has attracted the attention of investors all over the world, including Elon Musk who added Bitcoin to Tesla's balance sheet (Tesla SEC Filing 2021). In the SEC filing the company explained their purpose of their investment as a way to "further diversify and maximize returns on our cash". The company purchased roughly $1.5 billion of Bitcoin and even began to accept the cryptocurrency as payment for certain products. This decision was met with both praise and criticism, some people calling him a genius, some people calling him a madman. The mishmash of opinions on Tesla's Bitcoin purchase is exemplifying the need to further explore the role that Bitcoin plays in our current financial system.

The COVID-19 pandemic had a profound effect on global financial markets. In February 2020, the stock market began to crash as concerns about the COVID-19 virus intensified. In just about a month, from 2020-02-20 to 2020-03-23, the S&P 500 fell about 35% and the Bitcoin price plummeted around 37% during the same period. However, Bitcoin and the stock market was not the only markets to suffer greatly. As a particularly devastating example, the US oil prices crashed below $0 for the first time in history on April 2020 (EIA 2021). This crash certainly made many investors reevaluate what it truly means to be diversified.

To understand what role Bitcoin can play in an investment portfolio and to maximize the advantages of diversification, it's essential to understand if and to what degree a relationship between Bitcoin and other financial assets exist.

1.1 Problem Statement

The COVID-19 crash sparked my interest to explore financial markets and how they respond and interact in times of crisis. Through analysis of multiple financial graphs, I observed that Bitcoin and the stock market seemed to act very similarly during the pandemic. Another observation was that Bitcoin seemed to act much more as a high-risk asset (such as a stock) than a fiat currency (such as the USD). This led me to further question if Bitcoin really can be seen as a safe asset or not. ***Specifically, in this thesis I aim to evaluate if there is statistical evidence for or against Bitcoin as a safe haven asset.***

1.2 Definitions

It's essential that the reader of this thesis understands precisely what is intended by the terms "safe haven" and "recession" as the meaning of these words can vary depending on the context. Therefore, the definition of "safe haven" and "recession" that will be used throughout this paper will be explained in the subsequent sections.

1.2.1 Safe Haven

Safe haven is a widely used term in finance. In general, the term refers to some kind of investment that will either maintain its value, increase in value, or at least outperform other financial assets in an economic downturn. Classic examples of safe havens include gold, treasury bills and cash. In this paper, I will adopt the same definition as Baur & Lucey (2010) used in their paper on whether gold is a hedge or a safe haven. Baur and Lucey defines safe haven as ***a security that is uncorrelated with stocks and bonds during a market crash.***

1.2.2 Recession

Recently, as of writing this paper, there has been an ongoing debate about whether we are in a recession or not, as evidenced in Jamie Johnson's article "Are we in a recession?" (Jamie Johnson 2022). This debate has cast doubt on the exact meaning of recession. As the article outlines, a variety of experts have contrasting views on the matter. However, in general, a recession refers to a significant decline in economic activity. In this paper, I will use a rule-based definition rather than a linguistic one. I will adopt the definition provided by FRED (FRED Economic Data) to define recession and the period for the COVID market crash. FRED employs business cycle turning points calculated by the National Bureau of Economic Research (NBER) to distinguish recessionary periods. In this paper, the terms "recession" and "market crash" will be used synonymously.

1.3 Thesis Objective and Findings

The goal of this thesis is to identify whether we can find evidence for or against Bitcoin as a safe haven asset. To achieve this, an Engle and Granger cointegration test is performed to establish if a cointegration relationship can be found between Bitcoin and the S&P 500 index. If two variables are cointegrated, it implies that there exists a meaningful long-term relationship between them and that they tend to converge over time. Thus, if cointegration is found between Bitcoin and the S&P 500, it would provide evidence against the safe haven property (defined in section 1.2.2).

This study uses two datasets, the “COVID 19 Data Set”, which spanned from 2020-02-03 to 2020-04-01, and the “2016-2019 Data Set”, observed from 2016-01-04 to 2019-09-30. The former dataset is used to analyze the interaction of the variables during a market crash, while the latter is employed to compare the behavior of the variables in a more stable period. The primary findings of this paper show that a cointegration relation exists between Bitcoin and the S&P 500 in the first dataset but not the second. The implications of these results are discussed in chapter 6.

This thesis differs from prior research in that it provides a succinct and precise definition of the COVID-19 recession. To the best of my knowledge, no prior studies have adopted an identical time frame in the assessment of Bitcoin and its potential safe haven characteristics.

2 Previous Research

A great amount of research has been done on how volatility spreads between stock markets in times of crisis. One of many papers on the topic, by King and Wadhwani (1990), conclude that increasing volatility leads to an increase in the contagion effects between markets. A contagion is the spread of a financial crisis from one market/region/country to another. Their study has the October 1987 crash as their starting point and the increased correlation between world markets after that crash was used as evidence for how contagion increases as a result of increased volatility. Sandoval (2012) provides further support to the claim that high volatility of markets is linked to strong correlations. He investigated multiple crashes: the "Black Monday" crash of 1987 the "Russian Crisis" of 1998 the "dot-com bubble" of 2001 and the "subprime mortgage crisis" of 2008. A highlight of that paper is that a high correlation between stock markets is directly linked to the high volatility we see during financial crashes. This present thesis will aim to contribute and expand on this strand of literature by exploring how contagion spreads further between different types of financial markets. To be more specific, this thesis will explore if the high volatility during the COVID-19 crash of 2020 was linked to a stronger relationship between Bitcoin and the stock market compared to the period leading up to the crash (see the different data sets in chapter 5).

There is research supporting that volatility spreads between markets even though the markets operate at different times and are characteristically and geographically different. In another paper, the authors Lin, Engle and Ito (Lin, Engle and Ito 1994) explored empirically how returns and volatility correlated between the New York and Tokyo markets. They concluded that the information revealed during trading in one market had a global impact on the returns in the other. This paper is relevant to the present thesis because Bitcoin and the S&P 500 are very different markets and are open on different times (Bitcoin is open 24 hours, 7 days a week, while the S&P 500 is open from 9:30 am to 4 pm on weekdays only).

Previous research has also been done on whether Bitcoin in particular can be considered a safe haven or not. In a recent paper, Wen Tong and Ren (2022) conclude that Bitcoin could not be considered a safe haven for the stock market (S&P 500) and oil (WTI) during the COVID-19 pandemic. They used a different model than the one used in this paper (the TVP-VAR model) and a very similar definition of safe haven as the one used in this paper. The dates tested in their paper was between 2019-01-04 to 2021-06-04. Kumar and Padakandla (2022) also tested the safe haven properties of Bitcoin. Their goal was to test how suitable Bitcoin and Gold was as safe haven instruments using data spanning from 05-01-2015 to 31-12-2020 (including the COVID-19 crash). They tested Bitcoin against multiple different stock market indices and found varying results. They found that Bitcoin features safe haven properties in the short-run and long-run for NASDAQ and EUROSTOXX but not with the S&P 500. They used another methodology called wavelet quantile correlation. Both of these studies found that Bitcoin could not be seen as a safe haven when using S&P 500 data. However, the fact that one of them found safe haven properties in relation to other stock market indices is important to notice. This might be due to the different time frames employed in the studies. The use of different models might also contribute. In yet another paper, the authors López-Cabarcos et al. (2021) concludes that Bitcoin can be seen as a safe haven during high volatility. However, they used data collected from 2016 to 2019 so it's important to note that no major financial crisis happened during this time. As you will read in chapter 1.2.1, according to our definition of safe haven, a market crash must have been present to claim that an asset has safe haven properties. This further highlights that exploring different time periods can yield different conclusions. It also serves to emphasize how the interpretation of "safe haven" can heavily influence the results. López-Cabarcos et al uses a slight different definition of safe haven compared to this thesis, defining it as "an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil. ". The keywords here are "market stress" and "turmoil" compared to "market crash" which is the terminology used in the definition presented in chapter 1.2.1.

In this thesis, the Engle-Granger cointegration test was utilized. The method was formalized and introduced by Engle and Granger (1987). It's an approach to assess the presence of a long-term equilibrium relationship between two variables. There are several papers that adopt the Engle-Granger cointegration test to find out if two time series have a meaningful long-term relationship with each other. In a recent paper, Gallegati and Tamberi (2022) found the Engle-Granger approach suitable to use because they only had two variables to test and therefore only one co-integrating vector to find. The Engle and Granger test can only find one cointegrating relationship so it's not suitable for when you have more than two variables. If two or more variables are analyzed, another test such as Johansen's cointegration test can be used. The Engle-Granger method is also used in a recent study by Abraham C and Aileen L. (2021) to look for cointegration between interest rates and inflation to analyze if and to what degree the Fisher hypothesis is valid in the Philippines. Yet another example is a master thesis by Patrick Malm from Lund University (Malm 2018), where the Engle and Granger approach was used to find out if there existed any comovements between US and Chinese stock markets during and after the 2008 financial crisis. Malm also used the augmented dickey fuller test (ADF) to test for stationarity (the Engle-Granger and ADF-test will be used in this thesis)

3 Theoretical Framework

3.1 Bitcoin

Bitcoin is the largest cryptocurrency in the world measured by market capitalization (see for example coinmarketcap.com). An anonymous developer (or developers) under the pseudonym Satoshi Nakamoto introduced Bitcoin to the public in 2009. In the original thesis paper for Bitcoin called “Bitcoin: A Peer-to-Peer Electronic Cash System”(Bitcoin White Paper, 2008), Satoshi Nakamoto describes what Bitcoin is and why it is needed. In short, Bitcoin is a system for electronic transactions that solves the problem of trust that is always present in our current financial system. With standard electronic transactions, there always has to be financial institution acting as a trusted third party to process the payments. As an example, if I want to send $10 000 to someone, in say Africa, that would be a complicated process involving many third parties and trust. However, with Bitcoin, this is possible to do directly, in a peer-to-peer manner, where you have to trust no single entity, you only have to trust the Bitcoin protocol itself. By using cryptographic proof rather than trust, Bitcoin allows for two parties to transact directly without the need for financial institutions mediating the transactions. Bitcoin also solves the double spending problem (being able to spend the same digital currency twice or more) by using a process called proof-of-work. The Bitcoin network is secure as long as a majority of the participants are honest, and luckily, there is a strong incentive structure for participants to be just that. The process of verifying transactions is called “Bitcoin mining” because the miners, the ones performing the proof-of-work, are receiving Bitcoin as reward for keeping the network secure. The Bitcoin supply is fixed at 21 million (there will never be more than 21 million Bitcoin), which makes the currency “digitally scarce”.

The role of Bitcoin in the financial system is important to study because it’s a relatively new financial assets and its role in our financial system is still unclear. According to the U.S Commodity Futures Trading Commission (2015), Bitcoin and other virtual currencies are defined as commodities. For an asset to be a currency it needs to have three properties, it has to be (1) a medium of exchange (2) used as a unit of account (3) a store of value. However, according to Bariviera and others (Bariviera at al 2017), Bitcoin didn’t truly fulfill any of these properties by 2017. In their paper they state that Bitcoin is “an ideal asset for speculative purposes” rather than a currency.

3.2 S&P 500

The S&P 500 is an index made up of the 500 largest public companies in the U.S. The index is extensively regarded as the best measure of the large-cap U.S stock market (S&P 500 Factsheet 2022). Because the index gives a broad measure of the U.S stock market (it covers around 80% of the total available market cap), it’s a good index to use as benchmark for the U.S stock market as a whole. Since I want to compare Bitcoin with a broad measure of the U.S stock market, the S&P 500 is a good fit.

3.3 The Efficient Market Hypothesis

The Efficient Market Hypothesis, or EMH, is largely a further development of Muarice Kendall’s work from the 1950s. In 1953, Kendall found that he couldn’t identify any kind of predictable pattern in the stock market. At first glance, financial economists interpreted the results as evidence for that the stock market is erratic and dominated by market psychology, but upon further examination they concluded that the random movements Kendell found was evidence for the contrary, an efficient market (Bodie, Kane and Marcus 2014)

The Efficient Market Hypothesis was popularized by the economist Eugene Fama in a 1970 paper called “Efficient Capital Market: A Review of Theory and Empirical Work” (Fama 1970). In summary, the EHM states that asset prices reflect all information, or in other words, when new information becomes available, it will immediately be reflected in the asset prices. Fama defines an “informationally efficient” market to be a market where prices at each moment includes all information that is available about the future values. The hypothesis implies that trading rules based on both fundamental analysis and technical analysis should not work. Thus, trying to predict future asset values by looking at past prices and trading volume (technical analysis) or trying to analyze balance sheets, income statements, cashflows and so on (fundamental analysis) should be pointless.

Even though the efficient market hypothesis is highly influential and a cornerstone in modern finance, it’s also highly controversial. Miljan Lekovic (2018) discusses evidence for and against the efficient market hypothesis and concludes that even though the efficient market hypothesis has been under careful scrutiny for over half a century, the academic and scientific community is still far from reaching a consensus on the validity of the hypothesis. Warren Buffet, one of the most famous investors of all time has also argued against the hypothesis. In his article "The Superinvestors of Graham-and-Doddsville" Buffet argues that a very large proportion of a group of value investors beat the market on a consistent basis, an occurrence that is highly improbable according to the efficient market hypothesis (Buffet 1987).

The efficient market hypothesis can be divided into three categories: Weak-form, semi strong-form and strong-form. The difference between these categories lies in how "all available information" is defined (Bodie, Kane and Marcus 2014).

3.3.1 Weak-Form

The weak-form version of the efficient market hypothesis states that stock prices reflect all information about trading data. This includes information about prices, volume, short interest, and other data relating to technical analysis. The implication of the weak-form EMH is that no form of technical analysis can be used to guide your trading decisions. The theory builds upon the fact that past stock data is publicly available and easy to obtain.

3.3.2 Semistrong-Form

The semistrong-form of the EMH takes it one step further and states that prices reflect all public information about the stock. In addition to the trading data included in the weak-form version, the semistrong-form also includes fundamental information such as earnings forecasts, balance sheet analysis, quality of the management and so on. Neither technical analysis nor fundamental analysis can therefore be used to beat the market. Only non-public information can give investors an advantage according to this version of the EHM.

3.3.3 Strong-Form

The strong-form states that **all** information, technical, fundamental, and even insider information will be reflected in the stock prices. According to this form of the EMH, not even insiders with highly important, non-public information can profit from trading. This is an extreme take on the efficient market hypothesis and few would argue in favor of this version. There wouldn't be laws against insider trading if everyone would agree that the strong-form were indeed true.

4 Methodology

4.1 Econometric and Statistical Concepts

Let's start by looking at some important econometric and statistical concepts that will be needed to understand this paper.

4.1.1 Time Series

When observed data is indexed by date or time it's called a time series. Usually, time series has a starting point (t = 1) and ending point (t = T) and can be written as (Y_1, Y_2, . . . , Y_T), see for example James Hamilton (1994). Time series data is commonly represented by a graph. As an example of economic data represented by a time series, see the figure below (figure 1). The chart represents how crude oil prices changes over time. Stock prices graphed at daily intervals and heart rate graphed at perhaps millisecond intervals, are two other examples of time series. Time series plays a central role in domains that work with data over time, such as finance and macroeconomics.

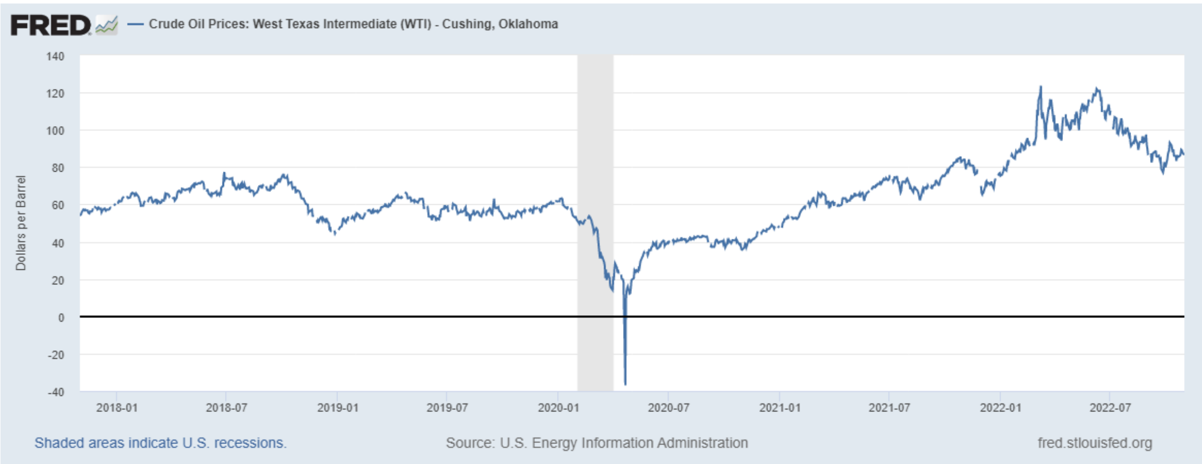
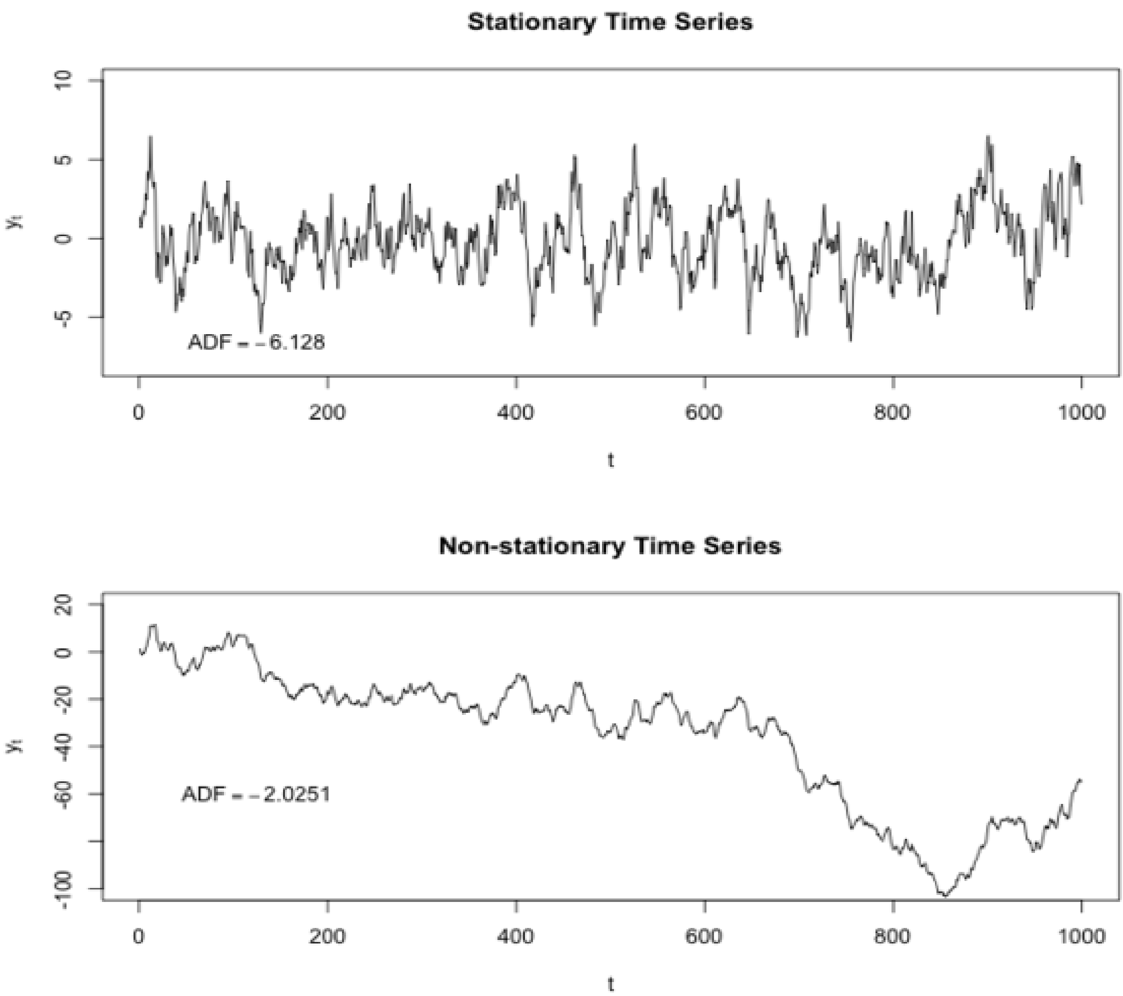


Figure 1 Crude Oil Prices: West Texas Intermediate (WTI)

Source: FRED Economic Data https://fred.stlouisfed.org/series/DCOILWTICO

4.1.2 Stationarity

A stationary time series is a special type of time series whose properties do not vary over time. No matter when you observe the time series, it should look very similar. As a consequence, the mean and variance of a stationary time series will be constant. Another property of a stationary time series is that the covariance between two time periods depends only on the gap between the two series and not the actual point in time where the covariance is measured (Gujarati 2003). Most financial and economic data is non-stationary as the mean and variance will vary over time. An example of a stationary time series and non-stationary time series can be seen in the charts below (figure 2). The upper graph seems to have a constant mean because the graph oscillates around 0. It’s harder to draw conclusions about the variance but here we can see that the time series seem to reach its highest values around 5 and lowest values around -5, and this pattern doesn’t seem to change over time. Both of these graphical clues indicates that it’s a stationary process (however, to confirm that it's indeed a stationary series it’s a good idea to use a statistical test). The opposite is true for the lower graph, it seems to have both a mean and variance that changes over time, indicating that it’s a



non-stationary time series.

Figure 2 Stationary and Non-stationary Time Series

Source: Wikimedia Commons

https://commons.wikimedia.org/wiki/File:Stationarycomparison.png

4.1.3 Unit Roots

A term that is very common in the time series literature and that will be used a lot in this paper is **"unit root"**. Mathematically a unit root is when **ρ=1** in the equation below:

$$\boldsymbol{Y_t = \rho Y_{t-1} + u_t \qquad -1 \leq \rho \leq 1}$$

Which means that the time series $\boldsymbol{Y_t}$ will depend exactly on the previous value of the time series $\boldsymbol{Y_{t-1}}$ plus a random error term $\boldsymbol{u_t}$. The error term has a mean of 0 and a constant variance $\boldsymbol{\sigma}^2$. When a unit root is present, the time series will be what is commonly referred to as a random walk and will be non-stationary. If, however, $\boldsymbol{1} \leq |\boldsymbol{\rho}|$, in other words, the absolute value of ρ is less than 1, it's possible to show that the time series $\boldsymbol{Y_t}$ will be stationary. To avoid confusion, the terms non-stationarity and unit root can be treated as synonyms (Gujarati 2003).

4.2 Statistical Tests

All statistical tests will be performed by *GRETL*, which is a free, open-source software package for econometric tests and analyses. The goal with performing these tests is to see if there were a statistically significant relationship the Bitcoin price and the S&P 500 during the COVID-19 crash (and the 2016-2019 Data Set). Since we are using time series data, it's not possible to simply regress one time series on the other. Regressing non-stationary time series can lead to spurious regressions, which are regressions that provide misleading evidence for a linear relationship. In their paper, Granger, and Newbold (1974), talk about the dangers of spurious regressions on time series data and that the usual tests for significance on the regression coefficients are invalid.

The methodology used in this paper can be divided into three parts, see for example Gujrati (2003)

(1) Test the first time series for stationarity by doing a unit root test. If the time series contains a unit root it's non-stationary. How this is done will be explained in chapter 4.2.1. Repeat the process for the second time series.

(2) After confirming that both time series are non-stationary (containing a unit root), we regress one time series on the other and save the residuals. The reason we do this is to see if we can estimate a cointegrating vector β such that the residuals themselves are stationary.

(3) Test the residuals for stationarity by using the same method as in (1). If there is no unit root present, we know that the residuals are stationary which implies that the time series are cointegrated.

Details on steps (2) and (3) are provided in section 4.2.2

4.2.1 Test for Stationarity

It's very often a good idea to view data graphically before performing tests. By doing that, you can develop an intuition for the data you are working with, and perhaps formulate a hypothesis for how your tests will turn out. In the case of testing for stationarity, it's often easy to see when a time series **is not** stationary. As mentioned in (4.1.2), in order for a time series to be stationary it has to have a constant mean and variance. Most of the time, it's relatively easy to detect a rising or falling mean by simply looking at the time series. Variance can be a bit trickier but it's usually also easy to detect non constant variance.

However, to make sure that we know if we are working with stationary or non-stationary data, it's a good idea to double check using a statistical test. There are many tests for stationarity but in this paper, I used the widely popular ADF test (Augmented Dickey Fuller Test). Dickey and Fuller (1979, 1981) developed a method to formally check stationarity in time series data. In (4.1.3) we talked about unit roots, and this test is basically testing the time series for the presence of a unit root. The test can be simplified as follows:

Start with the assumption that we are working with a unit root process:

$$\boldsymbol{Y_t = \rho Y_{t-1} + u_t \qquad -1 \leq \rho \leq 1}$$

For theoretical reasons that has to do with that both $\boldsymbol{Y_t}$ and $\boldsymbol{Y_{t-1}}$ are non-stationary under the null hypothesis, we have to manipulate the equation to:

$$\boldsymbol{\Delta Y_t = \delta Y_{t-1} + u_t} \text{ where } \boldsymbol{\delta = \rho - 1}$$

We then formulate our null hypothesis and alternative hypothesis as follows:

H0: δ = 0 => it contains a unit root => it's non-stationary

H1: δ < 0 => it contains no unit root => it's stationary

In order to know whether to accept or reject the null hypothesis (H0), we calculate a t-statistic and compare it to the critical dickey fuller value. If our t-statistic is less than the critical dickey fuller value, we reject the null. Alternatively, we can look at the p-value and reject the null hypothesis if our p-value is less than the critical p-value.

The critical value and the p-value will depend on what significance level we choose. For traditional reasons the 5% significance level will be used in this analysis.

4.2.2 Test of Cointegration - Elaboration of step (2) and (3)

In order to be able to perform regression analysis on time series data, the series must be stationary. The usual econometric t-tests and F tests are based on that assumption. Unfortunately, most economic time series are not stationary and will lead to nonsensical or spurious results if you simply regress them on each other. There are however some specific cases where we can meaningfully use regression analysis on time series data. Engel and Granger (1987) formalized and coined the term for an approach called cointegration.

Cointegration is when we have two non-stationary time series, but a stationary linear combination of these series exists. Or put it differently, if both of our time series contains a unit root, that is, they are individually **I(1)** but a stationary combination of them exists, in other words, a **I(0)** combination, we say that the time series are cointegrated. When time series are cointegrated, it suggests that there is a long run relationship between them.

4.2.3 The Cointegrating Regression

As stated in (4.2.2), you can't normally use an OLS regression on time series data unless the time series are stationary. An exception can be done when the variables are cointegrated. The cointegrating regression is not spurious even though the individual time series are **I(1).**

So, after confirming that the time series are indeed cointegrated we can run a normal regression using the standard OLS regression model:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

Where Y_i and X_i are our series

It's important to notice that the actual value of β_1 might not be interesting for our conclusion, because the focus of this paper is to investigate if there is a relationship between the time series and not necessarily what the relationship looks like. However, it is my belief that it could still be valuable to the reader of this paper.

5 Data and Analysis

5.1 Data

The analysis carried out in this paper uses secondary data, meaning that it's collected and made available by external parties. The data type is quantitative and continuous, that is, the data can be quantified and can theoretically take on any number. Time series data will be used for the analysis (see 4.1.1).

All the data used in the models and analysis comes from the FRED database (FRED Economic Data). This is an online database that contains more than 100 000 economic time series data from both national (US) and international public and private sources, covering for example numbers on CPI, GDP, money supply and stock prices. FRED has been providing data since 1991 and is considered a trusted source since it's one of the 12 regional reserve banks that makes up the US central bank, The Federal Reserve.

The two main data series that were used for this paper are "Bitcoin prices" and "S&P 500 values". To make for easier comparisons, I transformed both data sets to an index with a base number of 100.

The main dataset used for the analysis includes daily data from 2020-02-03 to 2020-04-01. The reasoning behind these seemingly arbitrary cutoff points is that FRED defines this period as a recession (FRED Economic Data). FRED uses business cycle turning points from NBER (National Bureau of Economic Research) to determine the start and end date for the recessions. The reason we are only interested in data from the recent recession is because the goal of this paper is to determine if Bitcoin can be regarded as a safe haven, and to test this, we don't necessarily need data from periods of prosperity. However, an additional dataset with daily data from 2016-01-04 to 2019-09-30 has also been used in a separate analysis. The results obtained using this alternative time period will be compared to the main data set in chapter 6. I will call the main data set the "COVID-19 Data Set" and the additional data set the "2016-2019 Data Set".

5.1.1 Bitcoin Prices (COVID-19 Data Set)

The Bitcoin data is obtained from FRED (FRED CBBTCUSD). All data is taken as of 5 PM PST and is based on a daily frequency. The Bitcoin market is always open, but to match the S&P 500 market, which is only open from Monday to Friday, we have excluded the Bitcoin data from the weekends. The FRED data for Bitcoin prices is based on the transactions happening on Coinbase, one of the largest cryptocurrency exchanges by trading volume in the US. In the figure below (figure 3) is the Bitcoin prices between 2020-02-03 and 2020-04-01 indexed so that it starts with a value of 100.

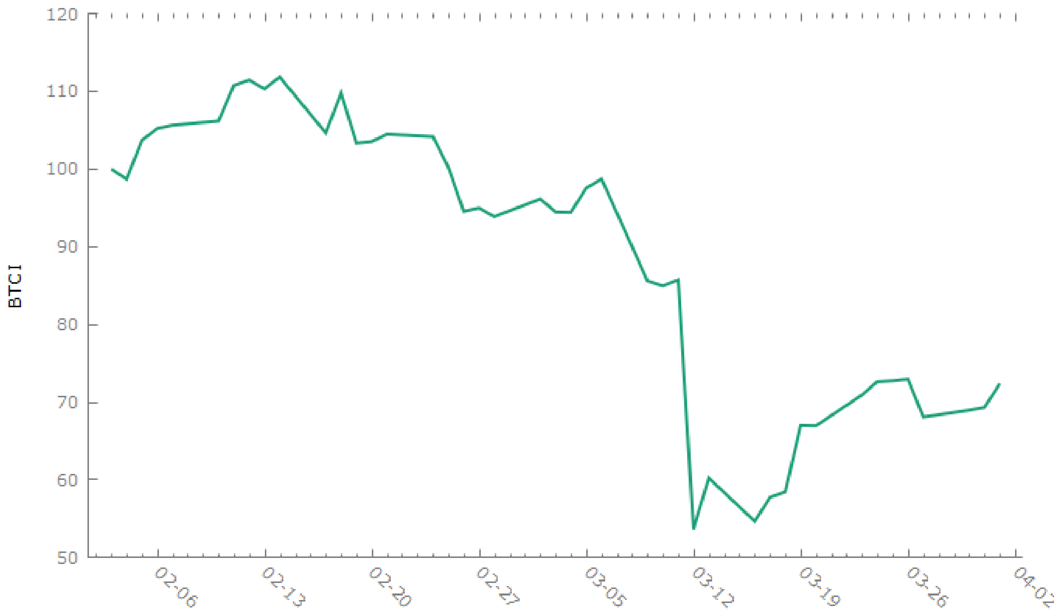


Figure 3 Bitcoin Prices

5.1.2 S&P 500 Values (COVID-19 Data Set)

The S&P values are also obtained from the FRED database (FRED SP500). The observations represent the daily S&P 500 value at market close (4 PM ET, with exceptions for holidays). The S&P 500 index includes 500 of the leading companies in the main industries in the United States economy. The S&P 500 is considered to be one of the best measures of the large cap U.S equities market. It’s important to note that the index is a price index and does not include total returns such as dividends. In the next figure (figure 4) is the S&P 500 values between 2020-02-03 and 2020-04-01 transformed to a starting value of 100.

Figure 4 S&P 500 Values

5.1.3 Bitcoin and S&P 500 Data (COVID-19 Data Set)

Below, in figure 5, is the charts from figure 3 and figure 4 graphed together.

Figure 5 Bitcoin & S&P 500 Values (COVID 19 Data Set)

5.1.4 Bitcoin and S&P 500 Data (2016-2019 Data Set)

In addition to the data above, I will analyze an additional data set with Bitcoin and S&P 500 values from 2016-01-04 to 2019-09-30. I will use these data to be able to compare it with the COVID-19 data set as well as being able to analyze it in light of the study by López-Cabarcos et al. (2021) about Bitcoin and the effect S&P 500 returns has on its volatility. The reason behind the cutoff points is because it's the same time frame used in their paper . The data I will be using here is daily data. The daily data for both S&P 500 and Bitcoin is based on the daily closing prices. Since Bitcoin is open 7 days a week and the S&P 500 is only open on weekdays, I had to do some changes to the data. All data for Saturdays and Sundays are excluded for the Bitcoin price, so the number of observations match the S&P 500 series. Another complication with the S&P data is that it has no values for holidays (public holidays or other non-working days where the stock market is closed). To solve for this issue, the previous data point will be used for days the stock market was closed. Like with the two main data sets, I also transformed these data sets to an index with a base number of 100 to allow for easier comparisons. Both the Bitcoin data and the S&P 500 data is taken from the FRED database (FRED CBBTCUSD, FRED SP500).

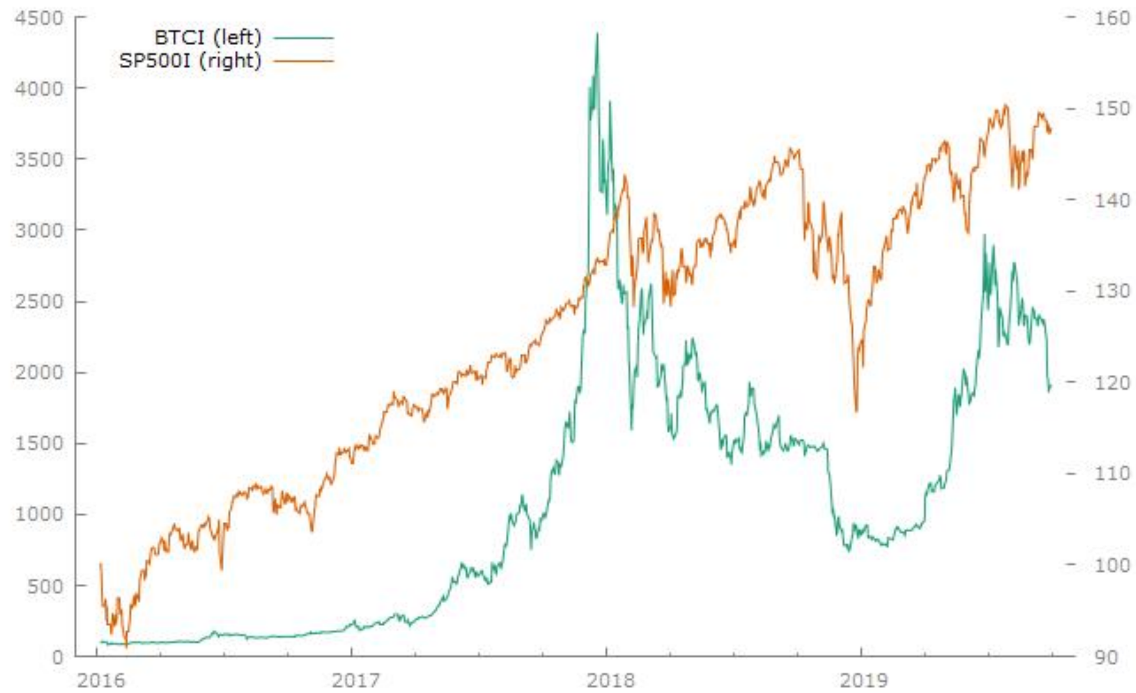


Figure 6 Bitcoin & S&P 500 Values (2016-2019)

Notice that the two axis are in different scales in figure 6, they both start at 100 but since Bitcoin covered a much wider range of values during the time period, it needs to have another axis.

5.2 Analysis

5.2.1 Unit Root Test (COVID-19 Data Set)

Below is our two main datasets BTCI and SP500I. BTC and SP500 refers to the time series used and the "I" is there to show that the data have been indexed to a common starting point. If you analyze the data graphically, you will quickly suspect that they are not stationary. Remember that in (4.1.2) I talked about that in order for a time series to be stationary, it has to have a constant mean and variance. By examining figure 5 (the same figure as on page 20) you can see that the mean for both time series seems to be not constant and is decreasing over time.

Figure 5 Bitcoin & S&P 500 Values (COVID 19 Data Set)

However, to confirm that the data is nonstationary, we will perform an Augmented Dickey-Fuller test (ADF). The program we use to perform the ADF test is GRETL.

The ADF-test results are presented below:

Variable	BTCI	SP500I
Test Statistic	-2.95	-2.59
P-Value	0.147	0.283

Table 1

The most important thing in table 1 is to look at the p-value. As stated in (4.2.1), the p-value used in this paper is 5%, meaning that the p-value has to be below 0.05 to reject the null hypothesis. We can read that the p-value for Bitcoin is 0.147 and the p-value for S&P500 is 0.283. Both p-values are larger than the critical value of 0.05 so we fail to reject the null in both cases. Remember from (4.2.1) that the null hypothesis (H0) is that the series contains a unit root (is non-stationary). So, the tests here confirm our suspicion (based on the graphical evidence presented above) that both time series are indeed non-stationary.

5.2.2 Cointegration Test (COVID-19 Data Set)

Now when we have determined that both of our time series BTCI and SP500I are non-stationary **I(1)**, it's time to perform out cointegration test. To do this, we need to for estimate the cointegrating regression. BTCI will be used as the dependent variable and SP500I and the independent variable. The reasoning behind this decision is that the goal of this thesis is to examine Bitcoin and more specifically if Bitcoin is a safe haven, so it makes sense to have Bitcoin as the dependent variable rather than the S&P 500. We will once again use GRETL to perform the regression.

The cointegrating regression results are presented below:

β_0	β_1	STD ERROR β_1	R^2
-43.3	1.45	0.0813	0.886

Table 2

As described in (4.2.3), the general equation for a regression can be written as follows:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

In our case, Y_i = BTCI, X_i = SP500I, β_0 = -43 and β_1=1.45. After inserting these numbers, we get:

$$\text{BTCI} = -43.3 + 1.45 * \text{SP500I} + \varepsilon_i$$

Which means that if the S&P 500 moves by 1, the model predicts that the Bitcoin price will move by 1.45. It's also worth to mention the constant term which is equal to -43.3. The model predicts that BTCI will take on a negative number if SP500I goes to 0, which makes no sense. The reason for this result is that we only tested BTCI for SP500I values in between 104 and 69 and it is not commonly possible to extrapolate models far beyond the scope of the data collected.

Also, the important result from this test is not the estimates of the regression parameters. The important result is the residuals from the regression and to perform an ADF test on those. As I mentioned in (4.2), if the residuals are stationary, it suggests that the variables are cointegrated.

The ADF test on the residuals is presented below:

Variable	Test Statistic	P-Value
u-hat (residual)	-4.58	0.00085

Table 3

As reported in table 3, the test statistic is small enough to give us a p-value of 0.00085. And as described in (4.2.1) we reject the null hypothesis (that the residuals contain a unit root) if the p-value is less than 0.05. Our p-value is much smaller than 0.05 so the null hypothesis is rejected with a level of significance for lower than 0.05. In other words. The tests are suggesting a statistically significant cointegration relationship between Bitcoin and S&P 500 during the time period considered.

5.2.3 Unit Root Test (2016-2019 Data Set)

The exact same methodology will be applied for this dataset. We start by looking at the graphs for BTCI and SP500I and suspect that they are non-stationary.

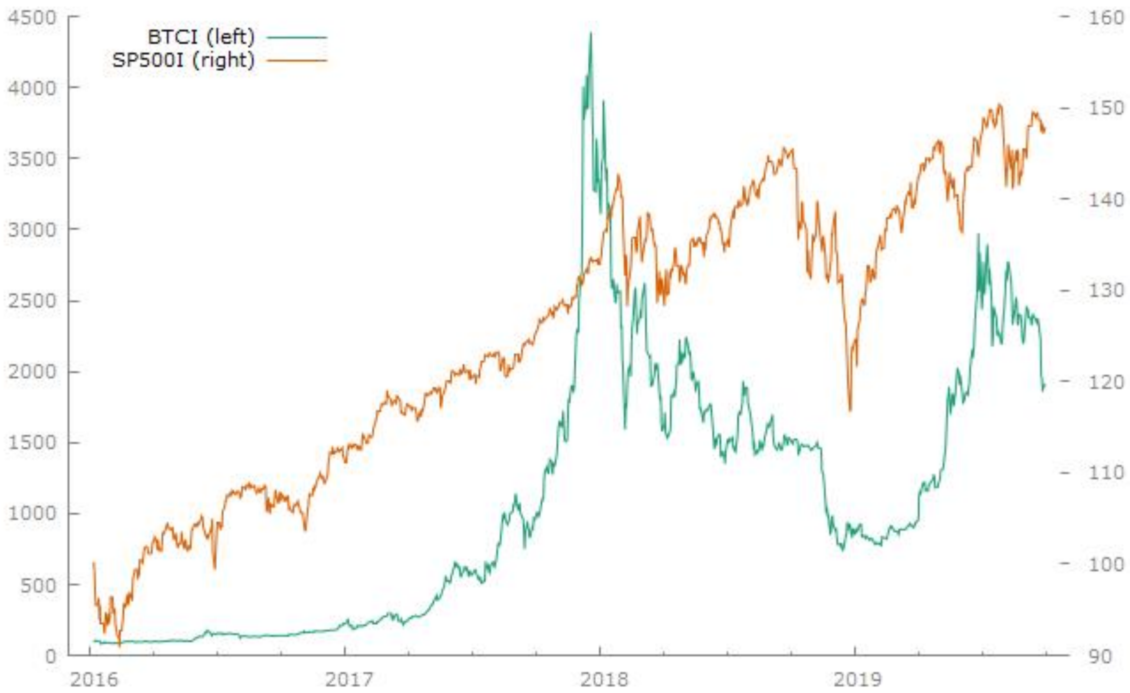


Figure 6 Bitcoin & S&P 500 Values (2016-2019)

To confirm that the time series are indeed nonstationary, we will once again perform ADF tests using GRETL.

The ADF-test results are presented below:

Variable	BTCI	SP500I
Test Statistic	-2.27	-3.15
P-Value	0.449	0.095

Table 4

By looking at the p-value for BTCI(2016-2019) and SP500I(2016-2019) we can see both are above the critical value of 0.05. The null hypothesis (that the time series a non-stationary) will therefor not be rejected. The ADF tests has confirmed our hypothesis that the time series are non-stationary.

5.2.4 Cointegration Test (2016-2019 Data Set)

As mentioned in (5.2.2), the important result from this test is not the regression values. The important result is to conduct an ADF test on the residuals from the regression. So, in this section I will only present the ADF test on the residuals (see appendix chapter 7.8 for the cointegrating regression).

The ADF test on the residuals is presented below:

Variable	Test Statistic	P-Value
u-hat (2016-2019)	-3.02	0.105

Table 5

The p-value is larger than the critical value of 0.05. This means that we fail to reject the null hypothesis that the residuals are non-stationary. This means that no statistically significant cointegration relationship was found between Bitcoin and S&P 500 during this time period.

6 Conclusion

A statistically significant cointegration relationship was found between Bitcoin and S&P 500 during the COVID-19 crash. This means that Bitcoin and the S&P 500 had a long-run equilibrium relationship during the timeframe. The goal of this thesis was to answer the question if Bitcoin can be regarded as a safe haven and according to our definition of safe haven, ***"a security that is uncorrelated with stocks and bonds during a market crash" ,*** this paper provides evidence against the safe haven property.

However, it's important to understand the limitations of the analysis. Since Bitcoin was created in 2009 and wasn't a mature market until some years later. The COVID-19 crash has been the first significant crash that Bitcoin has ever experienced, so this analysis should only be seen as a piece of evidence against the safe haven property and not as an established fact. The somewhat arbitrary choice of time frame for the data and the methodology are two other limitations to the study.

The two studies mentioned in chapter 2, Wen Tong and Ren (2022) and Kumar and Padakhandla (2022), both present evidence against Bitcoin as a safe haven when using S&P 500 data. However, the latter study did find that Bitcoin possess safe haven properties for NASDAQ and EUROSTOXX. This could be attributed to the fact that they used data over a longer length of time (05-01-2015 to 31-12-2022) compared to the Wen Tong and Ren (2022) study (2019-01-04 to 2021-06-04). Therefore, the COVID-19 crash was a much smaller portion of the Kumar and Padakandla study in comparison to the Wen Tong and Ren study, which may have contributed to them detecting safe haven properties for Bitcoin.

The second cointegration test in this thesis for the period 2016-01-08 to 2019-10-04 failed and no statistically significant cointegration relationship was found. This is evidence for the safe haven property. This result is compatible with the results from López-Cabarcos et al. (2021) who found that Bitcoin could act as a safe haven using data from the exact same period. It is important to note that during the (2016-2019 Data Set) no significant recession was present (according to the definition of recession used in this paper, see 1.2.2 & 4.2). So, the results from the (2016-2019 Data Set) is compatible with the earlier study from López-Cabarcos et al. (2021) but it doesn't affect our conclusion from the (COVID-19 Data Set). Another interesting insight from the analysis of the (2016-2019 Data Set) is that it is somewhat compatible with the Kumar and Padakandla (2022) study as well, who found safe haven properties for NASDAQ and EUROSTOXX during a somewhat similar time period.

When assessing whether Bitcoin can be regarded a safe haven, the definition of "safe haven" is essential, as the time period of studies on the topic and the results are influenced by it. In general, it seems like a more stringent definition of "safe haven" will lead to a more restricted time period for testing and thus making Bitcoin more likely to cointegrate with the S&P 500.

Let's return to the main result of this thesis, that we found a statistically significant cointegration relationship between Bitcoin and the S&P 500 for the period of 2020-02-03 to 2020-04-01. This finding appears to be in conflict with the efficient market hypothesis (EMH) even in its weakest form (see chapter 3.3.1), which says that no advantages can be derived from analyzing trading data as prices of assets already should reflect this information. The reason for this conflict, as Granger (1986) points out is that if two time series are cointegrated, one can be used to help predict the other and thus contradicting the efficient market hypothesis. If there is a true cointegration relationship between Bitcoin and the S&P 500, one could use this information to help guide trading decisions, such as not using Bitcoin as a hedge during a market crash.

Further research needs to be done to solidify the results of this paper. The stock market is currently experiencing a strong decline; thus, it is suggested that further research should be conducted to investigate the relationship between Bitcoin and the stock market during this current period. The data used in this paper was drawn from a single instance of a stock market crash, so to be able to gain insight about the true relationship (or at least, a likely relationship) between Bitcoin and the stock market during crashes, we need more data and more studies. Furthermore, it would be of interest to explore the relationship between Bitcoin and other financial assets such as gold, real estate and money supply. Although there has been prior research in these areas, because Bitcoin is still a relatively new asset, more research needs to be done to comprehend its role within our financial system.

7 References

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8 Appendix

This appendix reports additional calculations and the raw outputs from the statistical tests conducted in this thesis.

8.1 Silver's Market Cap

The silver market cap is calculated by multiplying the estimated silver mined (1,751,000 metric tonnes as of 2019) with the current silver price ($23.68 as of December 12 2022).

8.2 ADF Test Bitcoin (COVID-19 Data Set)

```
Augmented Dickey-Fuller test for BTCI
testing down from 4 lags, criterion AIC
sample size 38
unit-root null hypothesis: a = 1

  with constant and trend
  including 4 lags of (1-L)BTCI
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.408358
  test statistic: tau_ct(1) = -2.94853
  asymptotic p-value 0.1471
  1st-order autocorrelation coeff. for e: 0.010
  lagged differences: F(4, 31) = 2.125 [0.1013]
```

8.3 ADF Test S&P 500 (COVID-19 Data Set)

```
Augmented Dickey-Fuller test for SP500I
testing down from 4 lags, criterion AIC
sample size 39
unit-root null hypothesis: a = 1

  with constant and trend
  including 3 lags of (1-L)SP500I
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.330424
  test statistic: tau_ct(1) = -2.59412
  asymptotic p-value 0.283
  1st-order autocorrelation coeff. for e: -0.018
  lagged differences: F(3, 33) = 4.401 [0.0104]
```

8.4 Cointegrating Regression (COVID-19 Data Set)

```
Step 1: cointegrating regression

Cointegrating regression -
OLS, using observations 2022-02-03:2022-04-04 (T = 43)
Dependent variable: BTCI

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const       -43.3089     7.42418      -5.833    7.46e-07  ***
  SP500I        1.45497    0.0813329    17.89     5.63e-021 ***

Mean dependent var    88.40827   S.D. dependent var    18.28666
Sum squared resid     1595.040   S.E. of regression    6.237259
R-squared             0.886433   Adjusted R-squared    0.883663
Log-likelihood       -138.7036   Akaike criterion      281.4072
Schwarz criterion     284.9296   Hannan-Quinn          282.7062
rho                   0.561373   Durbin-Watson         0.876223
```

8.5 AFD Test on Residuals (COVID-19 Data Set)

```
Step 2: testing for a unit root in uhat

Augmented Dickey-Fuller test for uhat
testing down from 5 lags, criterion AIC
sample size 39
unit-root null hypothesis: a = 1

  test without constant
  including 3 lags of (1-L)uhat
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.803089
  test statistic: tau_c(2) = -4.58305
  asymptotic p-value 0.00085
  1st-order autocorrelation coeff. for e: -0.089
  lagged differences: F(3, 35) = 3.685 [0.0209]

There is evidence for a cointegrating relationship if:
(a) The unit-root hypothesis is not rejected for the individual variables, and
(b) the unit-root hypothesis is rejected for the residuals (uhat) from the
    cointegrating regression.
```

8.6 ADF Test Bitcoin (2016-2019 Data Set)

```
Augmented Dickey-Fuller test for BTCI
testing down from 10 lags, criterion AIC
sample size 966
unit-root null hypothesis: a = 1

  with constant and trend
  including 9 lags of (1-L)BTCI
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.00926528
  test statistic: tau_ct(1) = -2.27067
  asymptotic p-value 0.4495
  1st-order autocorrelation coeff. for e: 0.000
  lagged differences: F(9, 954) = 7.168 [0.0000]
```

8.7 ADF Test S&P 500 (2016-2019 Data Set)

```
Augmented Dickey-Fuller test for SP500I
testing down from 10 lags, criterion AIC
sample size 968
unit-root null hypothesis: a = 1

  with constant and trend
  including 7 lags of (1-L)SP500I
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.0215469
  test statistic: tau_ct(1) = -3.1489
  asymptotic p-value 0.09503
  1st-order autocorrelation coeff. for e: 0.005
  lagged differences: F(7, 958) = 2.593 [0.0119]
```

8.8 Cointegrating Regression and ADF Test on Residuals (2016-2019 Data Set)

```
Step 1: cointegrating regression

Cointegrating regression -
OLS, using observations 2016-01-04:2019-09-30 (T = 976)
Dependent variable: BTCI

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      -4794.71      143.534      -33.40    1.18e-163 ***
  SP500I        46.9709      1.14039     41.19    1.53e-215 ***

Mean dependent var   1072.348   S.D. dependent var   912.8490
Sum squared resid    2.96e+08   S.E. of regression   551.5753
R-squared            0.635274   Adjusted R-squared   0.634900
Log-likelihood      -7545.155   Akaike criterion     15094.31
Schwarz criterion    15104.08   Hannan-Quinn         15098.03
rho                  0.985223   Durbin-Watson        0.029608

Step 2: testing for a unit root in uhat

Augmented Dickey-Fuller test for uhat
testing down from 10 lags, criterion AIC
sample size 966
unit-root null hypothesis: a = 1

  test without constant
  including 9 lags of (1-L)uhat
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.0169749
  test statistic: tau_c(2) = -3.02075
  asymptotic p-value 0.1054
  1st-order autocorrelation coeff. for e: 0.001
  lagged differences: F(9, 956) = 4.746 [0.0000]

There is evidence for a cointegrating relationship if:
(a) The unit-root hypothesis is not rejected for the individual variables, and
(b) the unit-root hypothesis is rejected for the residuals (uhat) from the
    cointegrating regression.
```