What determines cryptocurrency prices: VAR and VECM approach

Dissertation submitted

by

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to

Department of Economics,
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in partial fulfilment of the requirements for the degree of

Master in Economic Analysis

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24.05.2022

Abstract:

The 2008-2009 Financial crisis, caused instability and uncertainty in the traditional financial system. People lost their trust towards the monetary system and were searching for better alternatives that could provide them with financial freedom and deregulation. The cryptocurrency network was the main alternative solution for many individuals. The benefits of the network being decentralised, secure and transparent brought many people together into one digital world. Individuals involved in this market are the ones who have the power to influence cryptocurrency prices and take control of their financial position. Examining how the prices of the three most popular cryptocurrencies, Bitcoin, Ethereum and Ripple are determined is thus essential. In this study, by using demand, supply and additional indicators, we are able to determine the price determinants of those three cryptocurrencies, in the short run and long run. Those three cryptocurrencies were created for entirely different purposes and entail different characteristics, thus our study provides the distinct results that define each one of them.

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1. Introduction

One of the remarkable developments in the financial world is the cryptocurrency evolution and in general the popularity of the three cryptocurrencies, Bitcoin, Ethereum and Ripple. Having in mind El Salvador as a country that has officially adopted Bitcoin as its currency, other countries that have previously experienced issues in the financial sector, may also follow this tactic. Based on financial times reports, El Salvadors' bonds have increased from 8,5 percent to 11 % just before the announcement of Bitcoin adoption, boosting confidence and increasing economic activity. Therefore, more and more countries are looking for intelligent ways to reset the traditional financial system to one that can be sustainable enough to overcome today's challenges. Although several cryptocurrencies tend to develop as time passes, the most prevalent ones are these three cryptocurrencies, Bitcoin, Ethereum and Ripple. Therefore, it is extremely important to examine the variables that affect their price movements. Significant price fluctuations have caused many individuals to profit by being part of the digitalized network, supporting the need of precisely predicting the factors that influence them.

By using Vector error correction model (VECM) and Vector Autoregressive models (VAR), the aim is to examine how demand, supply and other important indicators introduced in a later stage, affect the price of those three cryptocurrencies. Some of the variables tend to adjust at the same time. To take into account the endogeneity issue, we choose to employ the VAR and VECM models. Time series analytical tools are implemented in order to estimate both short run and long run effects. This enables us to compare short run and long run results for Bitcoin, Ethereum and Ripple.

Continuing, the data used for the econometric model is extracted from Google trends, Yahoo Finance, Ycharts, Nasdaq, Investing.com and Coinmarketcap, from January 2015 until October 2021.The data extracted from those sources are in monthly frequencies. The time frame is chosen accordingly, due to the fact that Ethereum was developed in 2015 and the inclusion of the coin in the study is important, as Ethereum is the 2nd higher trending cryptocurrency according to Coinmarketcap after Bitcoin. Bitcoin was introduced in 2008 and Ripple was introduced in 2012. Therefore, the choice of the data from 2015 is used since before that period data was unavailable due to limited transactions. Published data was made available after the cryptocurrencies became known to the public, which is from 2015 onwards.

Previous literature[1] on this topic relies greatly on Bitcoin price formation. The first major difference is that this paper tries to take into account not just how Bitcoin price is affected, but to also include Ethereum and Ripple which have been popular in the past few years.

[1] Pavel Ciaian, Miroslava Rajcaniova & d'Artis Kancs (2018) "The economics of BitCoin price formation"
Ladislav Kristoufek (2013) "BitCoin meets Google Trends and Wikipedia"

Most of the previous papers were analyzing Bitcoin performance or Bitcoin price formation without taking into account other cryptocurrencies. Therefore, similar focus needs to be shared amongst the three cryptocurrencies. Moreover, few papers include more than two variables in their econometric model to interpret price formation. My paper aims to include more than supply and demand indicators. Specifically, macroeconomic indicators and investment attractiveness are the two additional variables added apart from supply and demand indicators. Lastly, the main distinction of my paper is the econometric model used, as it allows the comparison of short run and long run effects.

Here is a short description of all of the indicators that are used in my regression analysis. They fall into three categories. First, we have the demand indicators captured by three variables, the inflation level, the size of each cryptocurrency economy and the level of velocity. Inflationary pressures are determined by the price level and are likely to affect cryptocurrency demand. In times of high inflation, cryptocurrencies can act as safe hedges and cause an increase in demand. Second, we have the size of each cryptocurrency economy captured by the activity in the cryptocurrency market which is likely to affect demand and thus price. Lastly, we have the velocity level measured by the frequency at which one unit of coin is used to purchase goods and services which also measures the demand of the coin and influences the price.

The supply indicator which can be interpreted as the coin market cap is captured by one indicator, the circulating supply. Circulating supply is the amount of coins freely moving into the cryptocurrency market. The coin market cap which is the total value of all the coins that have been mined is equivalent to the supply of the cryptocurrency. Therefore, it is not used as separate indicators as supply and market cap are equal. I also include two additional indicators as mentioned earlier. These are google search intensity that aims to capture the intensity people get informed about a specific cryptocurrency and thus its attractiveness and macroeconomic variables captured by the stock price index. The stock price index can affect cryptocurrency prices indirectly, by observing the market performance of companies that have or have not used the specific cryptocurrency as a source of payment.

The results conducted by the short run and long run relationships, the VAR and VECM models, give different predictions for the three different coins. For Bitcoin, our analysis shows that there is a positive correlation between previous Bitcoin prices and current Bitcoin prices supported by both VAR and VECM short run models, and we can also conclude that circulating supply can have a negative long run effect on Bitcoin since both VAR and the long run VECM support this result. However, our analysis on Ethereum price has shown that in the short run Ethereum price is affected positively by the lag level of velocity and past Ethereum prices and negatively correlated with past google search trends. However, in the long run there is an additional positive effect that comes from the inflationary pressures. And lastly, our analysis on Ripple price has shown that it is affected negatively by past velocity levels and past circulating supply in the long run and also in the short run but with an extra positive significant effect that comes from past google search intensity involving Ripple.

The structure of the paper is as follows. In Section 2, I include the literature review that presents the previous research papers that are closely related to my paper and how my paper differs. Furthermore, we continue with the theoretical and operational framework in Section 3 that introduces demand and supply determinants as well as macroeconomic indicators and investment attractiveness that are going to be used in the regression analysis. In Section 4 comes the Data Description where I add certain graphs that will help our understanding of how those coins have performed over the years. Section 5 includes the descriptive analysis in which the variables are introduced with the corresponding data sources. Then we have the Empirical and Analytical Methodology in Section 6 which describes the tests performed for my analysis. The data and results are included in Section 7 while the results are presented with the use of graphical representations in the last part, Section 8. Then we have the conclusion of the study in Section 9. The references are included in Section 10. Lastly, in the appendix, found in Section 11, I have included some other specification tests that were used to determine the appropriate model.

2. Literature Review:

Very few papers include the comparison of the three top cryptocurrencies while to the best of my knowledge no previous paper takes into account all the indicators involved in this paper. Ciaian, Rajcaniova & Kancs (2018) study focuses solely on Bitcoin price determinants, ignoring the huge advancements that have recently occurred in the cryptocurrency market. I think it is important to take into account the recent developments of the rest of the cryptocurrencies that absorbed some of Bitcoins' popularity. While some other studies use a more extended list of regressors in their econometric models, they still focus on Bitcoin only. Some of the regressors included in Kristoufek (2013) were how Google search volume and Wikipedia views have an impact on the price of Bitcoin. I also take into account how google search intensity affects the information people receive when researching for a specific cryptocurrency but in a slightly different way. Kristoufek (2014) in a later study includes some additional indicators, but only focuses on the Chinese market since Bitcoin is really popular in China. Specifically, the variables included in this study are money supply and demand, price level and trading volume. These variables are extremely important and I have included them in my analysis as well.

Other studies in the same context have been looking over trends in Twitter and how sentiment analysis affects the price of Bitcoin. Specifically, Sattarov, Jeon, Oh & Lee (2021) focus on Twitter's predictive power in the financial markets. In my paper, the inclusion of sentiment analysis is provided by the google search intensity of the specific cryptocurrency. The variable of google search intensity can better predict the power of how social media could affect cryptocurrency prices as it includes a wider range of social media platforms (Facebook, twitter, Linkedin, Instagram etc.) instead of focusing on just Twitter.

Continuing, a more recent study by Panagiotidis, Stengos and Vravosino (2018), the focus is still on Bitcoin determinants. Although they have used a lot of factors to investigate the determinants of Bitcoin, the study seems to be outdated when it comes to 2021, and needs to be reconsidered. Many events have happened since then that have potentially reformed some hypothesis results.

Furthermore, some studies took the step to add some more cryptocurrencies in their analysis such as Bitcoin, Tether, Ethereum, Litecon and EOS for the period 2017 until 2019 (Teker Teker & Ozyesil (2019). However, I avoid using coins such as Tether which is a stable coin, since its value is pegged on the U.S. dollar, and is designed to always be worth the equivalent amount. Moreover, I have also excluded Litecoin, which also uses the halving[2] feature during the mining process, and in its place, I have included Bitcoin to cover for that exclusion. Bitcoin is a much more powerful coin with similar mining characteristics. It could be a better representation of how those types of coins with the halving feature in place, do actually respond to changes in a variety of factors. Lastly, the last coin I would not include in this paper is EOS which is an ICO (initial coin offering) that uses its own block chain platform to develop, host, and run business applications. Even though EOS is currently used daily as an investment coin, it is similar to Ethereum. EOS was developed to provide a platform with smart contract capabilities and is one of the several alternative choices for Ethereum. Therefore, the choice was restricted to the use of Ethereum, Bitcoin and Ripple.

Generally, a lot of previous studies were focusing on Bitcoin price formation and using some of the regressors I also use. The huge number of papers focusing only on Bitcoin was because Bitcoin was the most popular cryptocurrency at that time. To cover this gap between the past and current period, this study aims to take into account the fact that during 2021, the digital market started altering the domination of specific cryptocurrencies, allowing Ethereum and Ripple to take part of Bitcoins attractiveness. Therefore, the paper focuses on Bitcoin, Etheeum and Ripple to show us a complete picture of what factors determine cryptocurrency prices and how they differ across them.

3. Theoretical and Operational Framework

As mentioned in Section 1, there are three sets of variables that potentially affect cryptocurrency prices: demand factors, supply factors and then other indicators.

Although demand and supply are the most crucial components when it comes to cryptocurrency price formation, according to Buchholz et al. and Bouoiyour and Selmi (2017), I also extend the analysis by adding two more indicators outlined in section 3.3 that can potentially explain cryptocurrencies.

Below, in Section 3.1, there is a list of the demand factors, followed by a list of the supply factors in Section 3.2 and then the two additional factors included in the model can be found in Section 3.3.

[2] Halving – the process of halving the rewards when mining a coin as more blocks are mined in order to keep price high and supply low

3. 1 Demand

The demand indicators are captured by the price level, the size of the cryptocurrency economy indicated by the volume of transactions and the level of velocity of each cryptocurrency.

- **Inflation**

Starting with the price level of goods and services in the economy, which is one of the demand determinants, it can be indicated by the inflation rate. If the price of goods and services is high, that means there is inflation in the economy. Cryptocurrencies, tend to act as hedging in times of inflation. Unlike traditional currencies, cryptocurrencies are deregulated and this feature makes them a perfect store of value. Taking Bitcoin as an example, it can act as a perfect inflation hedge due to its finite supply of 21 million. Ethereum and Ripple can also act as inflation hedges but Bitcoin could act as a better one due to its finite supply. When inflation is high, the value of traditional currencies depreciates. To overcome this depreciation problem, individuals invest in cryptocurrency assets that are predicted to rise in value at a higher rate than the inflation rate. The finite supply of Bitcoin can be one explanation for expecting its value to go really high. In this way, by investing in cryptocurrencies, individuals ensure that the net value of their assets remains positive even though inflation takes over the value of their traditional currencies. Therefore, we shall expect as inflation goes up, to see an upturn in cryptocurrency prices.

We use the exchange rate between the US dollar and the Euro to capture the inflationary pressures. This choice was made since the data of cryptocurrency prices is denominated in US dollars. Therefore, if the US dollar appreciates against the Euro then the Euro now can buy more dollars. Similarly the dollar would appreciate against the price of any cryptocurrency and therefore increase the amount of US dollars that have to be paid to buy one unit of cryptocurrency.

Another factor that affects inflationary pressures in the economy and therefore the demand for cryptocurrencies is political instabilities. Those instabilities can affect the inflation rate that will directly affect demand. Therefore, it is not included as a separate indicator but it is captured by inflationary pressures. Cryptocurrencies can act as hedging over political instabilities that resulted from high inflation rates. For example, inflation most of the time leads to uncertainty and poverty as money has less value. This results in lack of trust towards Central authorities, especially in countries with high social disruption levels and high levels of corruption. These countries include Zimbabwe, Argentina, and Venezuela. People residing in those countries were eager to explore the network of cryptocurrencies to provide them with financial freedom. Therefore, high inflation due to any reason will lead to an increase in demand for cryptocurrencies and this will reasonably affect positively their price.

- **Volume of transactions**

Second, demand for any cryptocurrency depends on the size of the specific cryptocurrency economy (Ciaina, Rajcaniova & Kancs 2015). This is indicated by the total volume of transactions. The higher the volume of transactions of Bitcoin for example, the more attractive will be for investors to get involved in the particular cryptocurrency and push the price upwards. The higher volume of transactions in Bitcoin market also causes higher volatility, because if more users trade at a specific time frame, then the more interesting it becomes for investors to trade and gain profits. Being more volatile means that there are more profitable opportunities for investors to buy at a lower price and sell at the highest price. Therefore, the higher the volume of transactions, the higher the volatility and the higher the liquidity of the coin. Bitcoin and Ethereum at the time of writing have the higher trading volumes in the cryptocurrency network according to CoinMarketCap. Both of these coins are more volatile than any other coin. Alternatively, XRP is 7th according to yahoo finance, as its main role, is to provide a form of payment and not solely to provide profits.

- **Velocity**

Thirdly, the last demand factor assumed to affect cryptocurrency prices is velocity. The velocity level of a specific coin measures the frequency at which one unit of coin is used to purchase goods and services. High velocity for a specific cryptocurrency means that individuals are willing to forgo their cryptocurrency assets to convert them to US dollars and buy goods and services. The opposite happens when velocity level of a specific cryptocurrency is low. Having in mind that selling a specific cryptocurrency leads to a downward pressure in price, we can conclude that high velocity levels will lead to lower cryptocurrency prices and low velocity levels will lead to high cryptocurrency prices. The best proxy to account for the velocity level of cryptocurrencies is the days needed for one coin to be destroyed.

Generally, cryptocurrencies are considered to be assets, meaning that individuals invest in them for the purpose of making money in the future. Therefore, velocity levels are considered to be extremely low. Cryptocurrencies are still growing and expected to increase in value therefore, it is reasonable for individuals to hold them for long periods of time. Evidence of this can be found by exploring the price of cryptocurrencies in CoinMarketCap. Bitcoin price has risen from $317.84 in 2015 to $60,683.19 in 2021. This shows that there was a huge increase in its value. Accordingly, Ethereum price increased from $0.873 in 2015 to $4,812.19 in 2021 and Ripple from $0.02256 to $3.0476 in 2017 and to $1.7661 in 2021. Therefore, it is clear that there were huge increases in value from 2015 until today, especially for Ethereum and Bitcoin.

3.2 Supply

Supply which is equal to the market cap of any cryptocurrency can be captured by the indicator of circulating supply.

Taking Bitcoin as an example, its supply is uniquely determined due to the fact that its supply curve is absolutely inelastic, meaning that any changes in demand would never change the quantity supplied and would only affect its price. Although current circulating supply is at 18,852,018 according to CoinMarketCap, it is rarely moving and steadily increasing in order to prevent reaching the limit of 21 million.

- **Circulating Supply**

Circulating supply is the amount of coins freely moving into the cryptocurrency market. Multiplying the circulating supply by the asset's price we get its market cap/ total supply. According to Coinbase, coin market cap or total supply is the total value of all the coins that have been mined. It is crucial to note that circulating supply and total supply/market cap are not the same. Not all coins that are mined or created are freely moving into the network for individuals to buy and sell, but some are held by private corporations or market makers. Equation 1 can summarize how circulating supply can affect total supply or the market cap:

$$Market\ cap\ or\ Total\ Supply\ =\ circulating\ supply\ x\ price\ of\ currency \qquad (1)$$

When it comes to how those factors affect cryptocurrency prices, cryptocurrencies with higher circulating supply or coins available in the market, are usually traded at cheaper prices due to the high availability. Bitcoin as an example currently holds at a circulating supply of about 18.9 million at the time of writing, Ethereum at 118,7 million and Ripple at 47.25 billion.

Therefore, according to equation 1, it is reasonable to assume that as price or circulating supply increases, market cap/total supply will also increase. The important thing here is that circulating supply and cryptocurrency prices will move in the opposite direction. The result on the market cap/total supply depends on which of the two has a larger effect.

3.3 Additional indicators:

Investors' attractiveness and Macroeconomic/Financial indicators:

The inclusion of supplementary factors that affect the price of cryptocurrencies is essential in order to formulate a complete regression model. Below there is a description of the two additional factors apart from demand and supply, which are investment attractiveness and macroeconomic or financial indicators.

- **Investors' attractiveness**

First of all, cryptocurrency prices are also affected by the risk or uncertainty of the digital network (Ciaina, Rajcaniova & Kancs 2015). Investment attractiveness will provide an estimate of how phycology plays a role in determining peoples' decision making. Previous events that happened in the market will have a direct effect on investors' expectations and attractiveness towards a specific cryptocurrency. Therefore, we need a factor that will capture these expectations. The way individuals get informed about news and updates is mainly through social media platforms, where most of the updates are published daily.

For example, investors who follow and expect news from one of the world's high profile figures, Elon Musk, will follow his tweets on twitter and he will have the power to influence the entire cryptocurrency network. Specifically, Elon Musk had the power to influence Bitcoin market by banning the use of Bitcoin for Tesla purchases in May 2021 to reduce the amount of fossil fuel used to mine those coins. As a result, this has led to a huge fall in Bitcoin price. Therefore, news and events are able to influence cryptocurrency prices either positively or negatively depending on the announcement made, the person who made it and the effect it has on investors' expectations.

- **Macroeconomic/Financial indicators**

Continuing with another variable that will be included in our regression analysis and that will help predict our price model, is macroeconomic and financial factors. In general the macroeconomic and financial factors will be a good representation of what is happening in the economy. The way to measure this effect is by including an indicator that would estimate the performance of big corporations and how their decision making will lead to changes in cryptocurrency prices. The variable used is the stock price index. This indicator may also have a positive or negative effect on cryptocurrency prices.

First, stock prices may affect cryptocurrency prices negatively. Falling stock prices can cause depreciation of the traditional currency but stimulate cryptocurrency growth. As stock prices fall, individuals tend to move to more profitable investments such as the cryptocurrency market. Therefore, in this case, financial assets are substituted for digital currency assets. This is the negative effect of how stock price index can influence cryptocurrency price.

However, when it comes to cryptocurrencies, there is a possibility of stock prices being positively correlated with cryptocurrency prices. This scenario happens when companies start accepting cryptocurrency transactions for the purchase of goods and services. Due to the reason that stock price index depends on the evolution of a specific corporation, the fact that many companies have started using cryptocurrencies as an alternative payment system, may lead to a positive correlation .Therefore, the decrease of stock price index may be an indication of the overall economy entering a downturn and corporations starting to face difficulties with maximizing their revenues. In this case, since part of the corporations' revenue comes from cryptocurrency transactions, this would cause cryptocurrency prices to follow the same pattern. An interesting example is Facebook partnering with Coinbase in order to introduce a digital wallet. This wallet will allow people to transact without any fees by using the digital wallet called Novi according to Cnet. Therefore, the result of stock market indices on the cryptocurrency value depends on the specific scenario taken into consideration.

3.4 Summing up the three sets of variables

Summing up the three sets of variables introduced in this section, we have demand being captured by the inflation rate which will potentially have a negative effect on cryptocurrency prices.

Next we have the volume of transactions that will positively affect cryptocurrency prices. The last factor of demand is the velocity level which will possibly have a negative correlation with cryptocurrency prices.

The supply factor that will also explain the market cap is the circulating supply. Circulating supply is expected to have a negative correlation with the cryptocurrency price. However, the exact direction is affected by both price and circulating supply as presented above in equation 1. And lastly, the two additional indicators, investment attractiveness and macroeconomic or financial indicators are expected to have either a positive or negative correlation with cryptocurrency price.

4. Data Description:

This section outlines all the variables, the corresponding coefficients and the source in which the data was obtained. Table 1 in the end of this section summarizes all the information included here.

Firstly, the price of each cryptocurrency is considered to be the exogenous variable as it is the variable we would like to estimate. Data for all three cryptocurrency prices is obtained from CoinMarketCap. The variable of cryptocurrency price P^C is denominated in US dollars in order to be comparable with the rest of the variables.

Next, we continue with the endogenous variables that are used to explain cryptocurrency prices. We have the demand equation, which is affected by the price level of goods and services, the volume of transactions and the velocity level. Starting with the general price level, inflationary pressures are captured by the exchange rate between the US dollar and the Euro, denominated by p_t. Then the second variable affecting demand is the volume of transactions during the specific period, represented by t_t in the regression equation. And the third factor which is the velocity level of each cryptocurrency, estimates the rate at which cryptocurrencies are exchanged to dollars. Therefore, the best proxy to account for the velocity level is the days needed for one coin to be destroyed given by v_t.

Continuing with the variables affecting the supply equation, we have the variable c_t which represents the circulating supply of each coin.

Furthermore, we introduced two additional indicators, which are investment attractiveness and macroeconomic/financial indicators that will help predict the model precisely. In order to measure investors' sentiment and model its power on cryptocurrency prices, we collect Google search trends related to each cryptocurrency separately. Previous studies were also supportive over using Social media activity by web search or google search to help predict the price of a cryptocurrency such as Matta, Lunseu and Marchesi(2015). Therefore, the variable of google search trends is used as it is assumed to be the first source of information for every individual.

The way google search intensity is estimated is by capturing how many times an individual searches using the name of each cryptocurrency. Investment attractiveness is represented by the variable a_t.

Lastly, and equally important, the macroeconomic/financial indicator is essential when it comes to predicting the future path of any cryptocurrency. Thus, in order to measure the effect of macroeconomic and financial developments on cryptocurrency prices, the additional variable that needs to be entered in the model is the Dow Jones stock market index. The index provides a measure of the industrial average of the biggest 30 US corporations on the Nasdaq and the New York Stock Exchange and it is one of the first and oldest stock indexes. This indicator is a precise measure of how healthy the US stock market is, and a good representation of the healthiness of the economy. As a result, this variable m_t, can capture the macroeconomic and financial position of the economy.

In table 1 there is a description of all the variables used, what they capture and the corresponding data sources. P^Ccorresponds to price of cryptocurrency, $p_t$corresponds to the inflation rate, $t_t$corresponds to the number of transactions, $v_t$corresponds to velocity and c_t corresponds to circulating supply, a_t corresponds to the google search intensity and lastly, m_t corresponds to the stock price index.

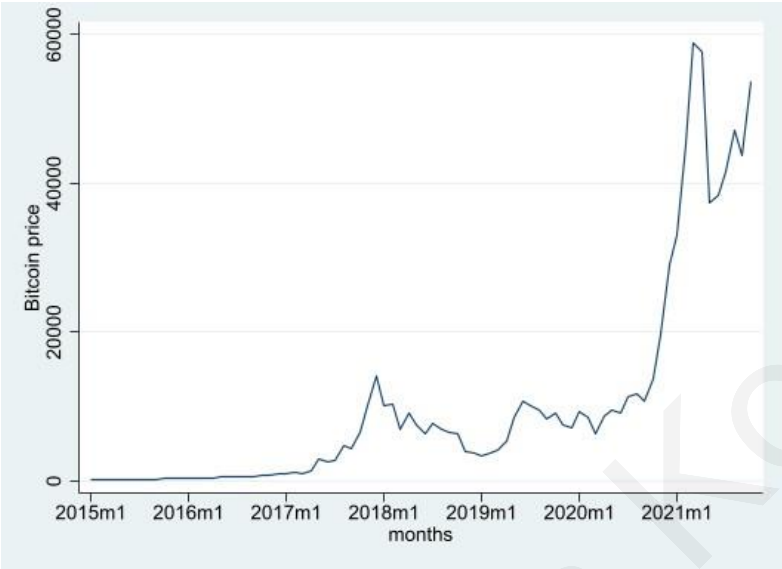
Table 1 – Variable description:

Coefficinets	Variables	What they capture	Data Source
P^C	Cryptocurrency price	Exogenous variable	CoinMarketCap
p_t	Exchange rate	Inflation rate	Investing.com
t_t	Volume of transactions	Size of Cryptocurrency Economy	Nasdaq
v_t	Days needed for one coin to be destroyed	Velocity level	Nasdaq
c_t	Circulating Supply	Coins freely moving	Ycharts
a_t	Google search intensity	Investment attractiveness	Google trends
m_t	Dow Jones stock market index	Macroeconomic/Financial indicator	Yahoo Finance

5. Descriptive Analysis

In this section I have included some graphs that will help our understanding of how the three cryptocurrencies have evolved over time. It is interesting to observe the direction of each cryptocurrency price pattern and provide a reasonable explanation behind it. First in Graph 1 we can see how Bitcoin prices have evolved from 2015 until 2021 and we can observe an overall increasing pattern.

Graph 1 – Bitcoin Price:



This is a graph showing how Bitcoin price has evolved from January 2015 until October 2021. Price of Bitcoin is shown on the vertical axis in US dollars and on the horizontal axis we have the monthly time frame. Price data is obtained from CoinMarketCap. Bitcoin price has increased from $217 to $58918.

Graph 1 shows a steady price movement from 2015 until mid-2017 where we observe an increase in price from $1000 to almost 20K in 2018 and rising up to 60K in late 2020 with some downward movements in early 2021.Overall Bitcoin prices have increased from $100 to approximately 60K in February 2021.

As mentioned earlier, part of the downturn in price in early 2021, can be explained by the crisis that the Bitcoin market faced. Despite the small ups and downs in price, Bitcoin fell below 41K in March 2021. News and events that happened during that period were the catalysts for this dramatic fall. First, it was presidents' Joe Biden approval of a new order that aimed to regulate the development of cryptocurrencies. Second, Elon Musks' new regulation to ban the use of Bitcoin for Tesla purchases played a role in Bitcoins' downturn. However, we observe that there was an increase in price from December 2021 onwards and price has risen above 50K. This increase in Bitcoin price could be explained by the surge in inflation during the pandemic period and the lagging recovery in the employment sector. Therefore, users' attention was turned towards Bitcoin to fight against the high rates of inflation. Experts believe that the increase in Bitcoin price will continue until it hits 100K which is predicted to happen in 2022 (DeMatteo 2022).

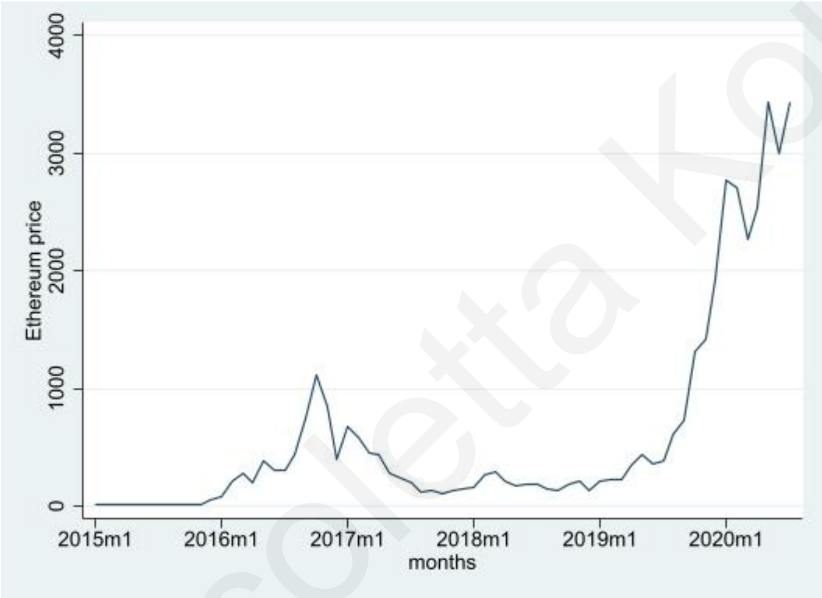
Below we can see the table summarizing the descriptive statistics for Bitcoin. We can observe that the lowest price was $217 while the higher price was $58918 which is almost 60K as mentioned previously out of 82 observations. We also have the mean value at the price of $10271.83 and the standard deviation at 14477.71.

Table 2 – Bitcoin Descriptive Statistics:

Variable	**Observations**	**Mean**	**Standard deviation**	**Minimum Price**	**Maximum Price**
Bitcoin Price	82	$10271.83	14477.71	$217	$58918

Next we observe a similar pattern in the price of Ethereum but in a completely different scale. There is an increasing pattern of Ethereum price over time with spikes in late 2017, when the price has gone above 1K and a huge spike in 2021, when price has reached almost 4K.

Graph 2 – Ethereum Price:



This is a graph showing how Ethereum price has evolved from January 2015 until October 2021. Price of Ethereum is shown on the vertical axis in US dollars and on the horizontal axis we have the monthly time frame. Price data is obtained from CoinMarketCap. Ethereum price has increased from $8 up to $3432.

Etherum has followed a similar pattern to Bitcoin. Despite the fact that Bitcoin and Ethereum were created for entirely different purposes, their price cycle behaved in a similar way. Ehereum provides a platform for other coins to be developed, using the same blockchain as the one Ethereum was built on. These tokens are built on the Ethereum network such as Solana, Cardano, Polkadot and even Ripple. The rise in Bitcoin from late 2020 until 2021 incentivised the creation of more Etherium based coins causing the price of Ethereum to increase. This also shows that Bitcoin is the first mover when it comes to changes in cryptocurrency prices.

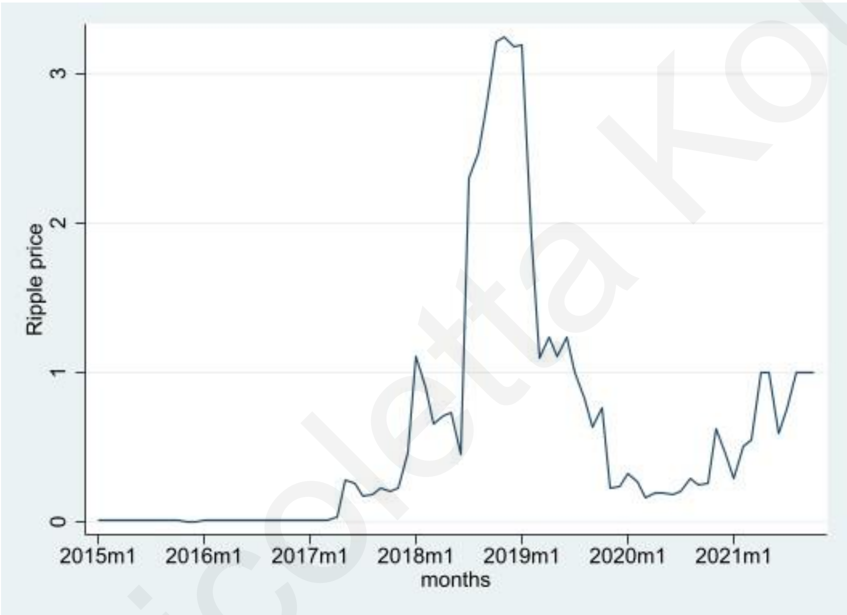
In table 3, we observe the descriptive statistics for Ethereum, having the minimum price at $8 and the maximum price at $3432. The mean value is at $590.209 and the standard deviation is at the value of 871.3042, much lower than Bitcoins' standard deviation.

Table 3 – Ethereum Descriptive statistics:

Variable	Observations	Mean	Standard deviation	Minimum Price	Maximum Price
Ethereum price	82	$590.209	871.3042	$8	$3432

Below we also have the graph for Ripple price. The price pattern is different than the upward pattern we observe in Bitcoin and Ethereum. For Ripple we can see that there was a huge spike in mid-2018 when price reached from $0,000 to $3, 1996 and then fell back to $0,2066 in 2020 until it rose to $1,4 in 2021.

Graph 3 – Ripple price:



This is a graph showing how Ripple price has evolved from January 2015 until October 2021. Price of Ripple is shown on the vertical axis in US dollars and on the horizontal axis we have the monthly time frame. Price data is obtained from CoinMarketCap. Ripple price has increased from $0.0043 to $3.24.

Ripple was created for the purpose of providing quick and secure online currency exchanges. This was the reason that Ripple went into court by the SEC (Securities and Exchange Commission) with the argument questioning whether Ripples' token, XRP, is classified as a security under the securities laws. Ripples' victory over the battle has caused the surge in price. The court has denied SEC accessing Ripples financial records and stated that Ripple should be treated as Bitcoin or Ethereum, having in mind that neither of the two are subject to any SEC lawsuit.

Moreover, we also observe a huge fall in price in 2019 and this can be explained by the decision of Coinbase to suspend XRP trading. This decision could be explained by the recent event of Ripple filing to the public. Therefore, people could not trade XRP token through Coinbase, one of the largest exchange platforms, which may have resulted to the dramatic fall in price.

Lastly, table 4 summarizes the descriptive statistics for Ripple. Below we observe that the minimum price of Ripple was $0.0043 while the highest price reached was $3.24 and the mean value is at $0.5911963. The standard deviation is expected to be much lower at 0.8269094, even though there were sudden price spikes. Ripple price was only able to reach the price of $3.24, which is a much smaller increase in price compared to Ethereum and Bitcoin increases.

Table 4 – Ripple Descriptive Statistics:

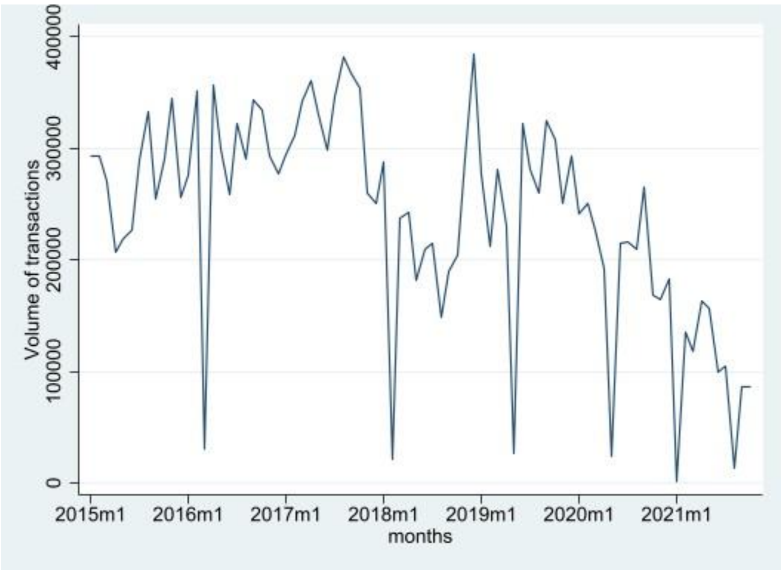
Variable	**Observations**	**Mean**	**Standard deviation**	**Minimum price**	**Maximum Price**
Ripple Price	82	0.5911963	0.8269094	$0.0043	$3.24

Comparing the price cycles of the three different cryptocurrencies, we observe a much smaller variation in the price of Ripple compared to the price variation of Bitcoin and Ethereum. This smaller increase from $0.0043 to $3.24 as shown in table 4, confirms that Ripple was a cryptocurrency created to act as a means of initiating transactions and aims to keep a more stable value over time. On the other hand, Bitcoin and Ethereum, considered to be investment coins, are expected to face larger price fluctuations in order to allow individuals to gain from investing in those digital assets.

Comparing the standard deviations across the three coins in Tables 2, 3 and 4, we observe that Bitcoin has the highest standard deviation at 14477.71, followed by Ethereum with a value of 871.3042 and last we have Ripple at 0.8269094. This shows that Bitcoin prices are more dispersed in relation to the mean value of $10271.83 and have more variability. Ripple has the lowest standard deviation. Therefore, the prices are clustered around the mean of $0.5911963. Indeed price reached the maximum price of $3 at one specific period and after that, the price was always below $1 and thus close to the mean value.

This variability in prices can also be explained by observing the volume of transactions in the Bitcoin market. In graph 4 we can see that there is a huge variability in the volume of transactions over the specified time frame causing the price of Bitcoin to continuously go up and down. Moreover, we observe the volume of transactions steadily following a downward pattern. The reasoning behind this may be due to the introduction of new coins into the digital network that slowly became popular taking over Bitcoins’ attractiveness.

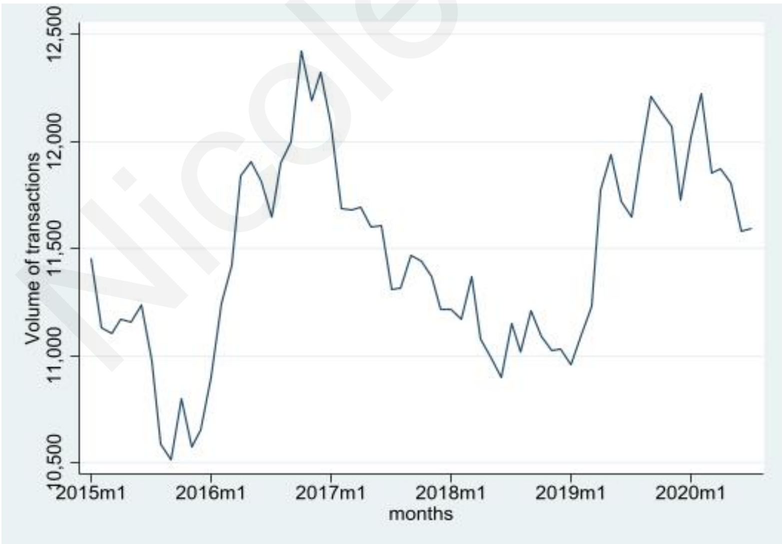
Graph 4 –Bitcoin Volume of Transactions



This is a graph showing Bitcoin volume of transactions from January 2015 until October 2021. Volume of transactions is indicated on the vertical axis and on the horizontal axis we have the monthly time frame. Volume of transition data is obtained from CoinMarketCap. Bitcoin volume of transactions has increased up to 400000.

In contrast, Ethereum and Ripple volume of transactions experience less variability due to the price being steadier and close to the mean value. Having Etherum price experiencing some variability in price, we expect to see the transaction volume graph being somehow flatter than the Bitcoin transaction volume graph. In graph 5 we can see the volume of transactions for Ethereum.

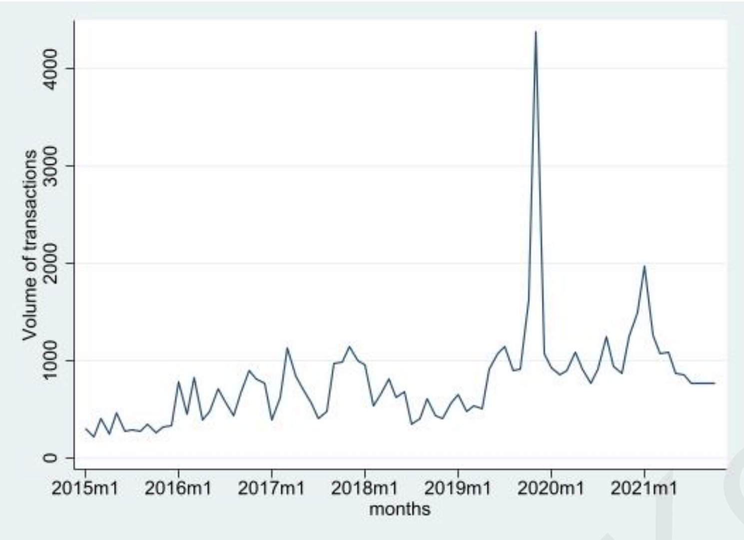
Graph 5 – Ethereum Volume of transactions



This is a graph showing Ethereum volume of transactions from January 2015 until October 2021. Volume of transactions is indicated on the vertical axis and on the horizontal axis we have the monthly time frame. Volume of transition data is obtained from CoinMarketCap. We can observe a flatter pattern for Ethereum volume of transactions compared to Bitcoin volume of transactions. Ethereum volume of transactions has increased up to 12500.

And lastly Ripple price has the smallest standard deviation and variability therefore we observe a flatter-shaped pattern for the volume of transactions which is outlined in graph 6. We also observe a huge rise in the volume of transactions in 2020 when the price dropped after the huge rise in 2019. This drop in price incentivised many individuals to buy XRP tokens expecting price to boost.

Graph 6 – Ripple Volume of transactions:



This is a graph showing Ripple volume of transactions from January 2015 until October 2021. Volume of transactions is indicated on the vertical axis and on the horizontal axis we have the monthly time frame. Volume of transition data is obtained from CoinMarketCap. We can observe a flatter pattern for Ripple volume of transactions compared to Bitcoin and Ethereum volume of transactions. Ripple volume of transactions has increased up to 4000.

6. Empirical and Analytical Methodology

By taking into account supply, demand factors and the two additional indicators, equation 2 can be formulated in order to be able to determine the price of a cryptocurrency. The model is formulated as follows:

$$P^c = \beta_0 + \beta_1 p_t + \beta_2 t_t + \beta_3 v_t + \beta_4 c_t + \beta_5 a_t + \beta_6 m_t + \varepsilon_t \qquad (2)$$

The coefficient $\beta_1$corresponds to the price of goods and services, β_2 corresponds to the size of cryptocurrency economy, β_3 to cryptocurrency velocity and β_4 to cryptocurrency circulation. The empirical explanations of coefficients come from the theoretical assumptions made earlier, β_1 and β_2 should be positively related with the price. Continuing with β_3 and β_4, should be negatively correlated with cryptocurrency price.

The coefficient β_5 captures the effect of investment attractiveness on cryptocurrency price and could be either positive or negative depending on the news published on social media. Moreover, the coefficient β_6 that captures the effect of stock price index on cryptocurrency prices can be either positive or negative.

Therefore, the complete regression model can be estimated by equation 2 which includes all the variables used in the analysis.

In order to calculate how the price of Bitcoin, Ethereum and Ripple is affected by the variables introduced in equation 2, monthly data is used from January 2015 until October 2021. Stationarity and co-integration tests are undertaken to test whether it is applicable to use VAR or VECM model to calculate the relationship. The VAR model will estimate the short run relationship while the VECM will estimate both the short run and long run relationships.

According to Sims (2011), due to the fact that the variables depend on one another, there is interdependence between them. In order to prevent the issue of simultaneity, all variables should be treated the same way. Once this restriction is used, all variables are treated as endogenous due to the reason that all variables can cause each other. Therefore, each variable can be used as a dependent variable in each equation and can be explained by the rest. This will lead to seven separate equations accordingly. For example, in the first equation shown below, equation 3, the price of the cryptocurrency is treated as the dependent variable, and the rest of the variables are treated as the independent variables. Moreover, the lagged variables are included in the model, since past values tend to affect current values. The appropriate lag length to be used for each cryptocurrency will be tested by some lag length criteria in the proceeding stages. Continuing, with the rest of the equations, equation 4 takes the general price level as the dependent variable and the rest variables as the independent ones. In this way, we have 7 different regression equations, each time treating each variable as the dependent variable.

$$P^c = \beta_{10} + \beta_{11}p_t + \beta_{12}t_t + \beta_{13}v_t + \beta_{14}c_t + \beta_{15}a_t + \beta_{16}m_t + \gamma_{11}p_{t-1} + \gamma_{12}t_{t-1} + \gamma_{13}v_{t-1} + \gamma_{14}c_{t-1} + \gamma_{15}a_{t-1} + \gamma_{16}m_{t-1} + \gamma_{17}P^c_{t-1} + \varepsilon {P^c}_t \qquad (3)$$

$$p_t = \beta_{20} + \beta_{21}P^c + \beta_{22}t_t + \beta_{23}v_t + \beta_{24}c_t + \beta_{25}a_t + \beta_{26}m_t + \gamma_{21}P^c_{t-1} + \gamma_{22}t_{t-1} + \gamma_{23}v_{t-1} + \gamma_{24}c_{t-1} + \gamma_{25}a_{t-1} + \gamma_{26}m_{t-1} + \gamma_{27}p_{t-1} + \varepsilon p_t \qquad (4)$$

$$t_t = \beta_{30} + \beta_{31}p_t + \beta_{32}P^c + \beta_{33}v_t + \beta_{34}c_t + \beta_{35}a_t + \beta_{36}m_t + \gamma_{31}p_{t-1} + \gamma_{32}P^c_{t-1} + \gamma_{33}v_{t-1} + \gamma_{34}c_{t-1} + \gamma_{35}a_{t-1} + \gamma_{36}m_{t-1} + \gamma_{37}t_{t-1} + \varepsilon t_t \qquad (5)$$

$$v_t = \beta_{40} + \beta_{41}p_t + \beta_{42}P^c + \beta_{43}t_t + \beta_{44}c_t + \beta_{45}a_t + \beta_{46}m_t + \gamma_{41}p_{t-1} + \gamma_{42}P^c_{t-1} + \gamma_{43}t_{t-1} + \gamma_{44}c_{t-1} + \gamma_{45}a_{t-1} + \gamma_{46}m_{t-1} + \gamma_{47}v_{t-1} + \varepsilon v_t \qquad (6)$$

$$c_t = \beta_{50} + \beta_{51}p_t + \beta_{52}t_t + \beta_{53}v_t + \beta_{54}P^c + \beta_{55}a_t + \beta_{56}m_t + \gamma_{51}p_{t-1} + \gamma_{52}t_{t-1} + \gamma_{53}v_{t-1} + \gamma_{54}P^c_{t-1} + \gamma_{55}a_{t-1} + \gamma_{56}m_{t-1} + \gamma_{57}c_{t-1} + \varepsilon c_t \qquad (7)$$

$$a_t = \beta_{60} + \beta_{61}p_t + \beta_{62}t_t + \beta_{63}v_t + \beta_{64}c_t + \beta_{65}P^c + \beta_{66}m_t + \gamma_{61}p_{t-1} + \gamma_{62}t_{t-1} + \gamma_{63}v_{t-1} + \gamma_{64}c_{t-1} + \gamma_{65}P^c_{t-1} + \gamma_{66}m_{t-1} + \gamma_{67}a_{t-1} + \varepsilon a_t \qquad (8)$$

$$m_t = \beta_{70} + \beta_{71}p_t + \beta_{72}t_t + \beta_{73}v_t + \beta_{74}c_t + \beta_{75}a_t + \beta_{76}P^c + \gamma_{71}p_{t-1} + \gamma_{72}t_{t-1} + \gamma_{73}v_{t-1} + \gamma_{74}c_{t-1} + \gamma_{75}a_{t-1} + \gamma_{76}P^c_{t-1} + \gamma_{77}m_{t-1} + \varepsilon m_t \qquad (9)$$

This interdependence between the variables may lead to spurious results. In order to avoid having a spurious regression, the stationarity of the time series variables is tested. In theory, spurious regressions may appear when the variables included are shown to be related without any actual relationship between them. Therefore, we proceed with the stationarity tests for all the seven variables.

6.1 Stationarity tests:

In order to test for unit root in the time series model, the two most commonly used tests are applied, the Dickey and Fuller test (1979) and the Phillips and Perron test (1988). These tests are included in the apendix under the specification tests of each cryptocurrency. The null hypothesis fails to be rejected if there is a unit root in the model. Previous studies have shown some distinctions between the acceptance and rejection region areas of the two tests. Even if using the exact same data set, the two tests may show some variations. However, due to the fact that the Phillips and Perron test is found to reject the null less often than the Dickey Fuller test (Leybourne and Newbold 1999) both tests are examined and in this way the Perron test is confirming the stationarity of the Dickey Fuller test.

Furthermore, the issue of the variables being unpredictable and not easily forecasted can be dealt with by estimating the variables in differences. Non stationary variables in levels can be converted into their differences in order for them to be modeled and ensure their stationarity. Therefore, the regressors in levels are converted to regressors in differences to ensure the stationarity of the variables.

6.2 Co-integration tests.

Co-integration tests are undertaken in order to determine which model is the appropriate one to be used, VAR or VECM. If results show that there is no co-integration relationship then the model is estimated by VAR. However, if results show that a co-integration relationship exists, then the VECM model is used and calculates the short run and long run relationships. Cryptocurrency prices in general tend to move occasionally and are usually experiencing sudden changes, especially the more volatile cryptocurrencies. In these cases, sudden changes in price tend to alter the overall direction of the price trend before it reverts back to normal. Therefore, it is often the case of finding points which are a bit anomalous compared to the majority of the price movements. Taking Ripple as an example, in graph 3 previously outlined, it appears that there was a sudden increase in price in 2019 that was only held for a small period of time before reverting back to the normal price pattern. The issue with this is that the least square regression will provide statistically significant slope parameters ignoring the sudden short run changes in the overall trend. Therefore, the idea is to introduce co-integration in the model with the possibility of having a true relationship between any two variables that holds over time.

When two or more series are stationary, then standard OLS estimator can be used to predict the model. This however is not the case in our model since we observe sudden jumps in our variables.

If two or more time series tend to be non-stationary then their combination may lead to stationarity series and therefore the variables being co-integrated. This means that there is truly a long run relationship between the two variables and the Vector Error Correlation (VECM) model is the appropriate method of estimation. The VECM model estimates both the short run and long run relationships. When having a mixture of non-stationary variables and non-co-integrated variables, meaning there is no true long run relationship between the two series, then the VAR model is the appropriate method of estimation.

Table 5 summarizes which model should be used in each case.

Table 5 – OLS/VEC/VAR

2 series			
Stationary	Co-integrated	True relationship exists	OLS
Non Stationary but combination is stationary	Combination is co-integrated	True long run relationship exists	VECM
Non stationary and combination non stationary	Non co-integrated	No true long run relationship	VAR

In order to test for the stationarity of the series, the Johansen co-integration test is used under the specification tests in the apendix. The fact that the Dickey Fuller and Phillips Perron tests are not used in the co-integration scenario is due to the reason that they were suggested to have lower power when there appears to be serial correlation. Even though all of the tests, including the Dickey Fuller and Perron tests are performed in the paper, we will rely on the Johansen co-integration test. The Johansen co-integration test was developed by Soren Johansen (Floyd 2013) . This test also has the advantage of finding co-integration relationships without hinging the results based on the decision of dependent variable. In our case, this is the best stationarity test since each time the depended variable will be a different variable.

The Johansen co-integration is as follows:

$\mathrm{H_0}$: no co − integration

$\mathrm{H_1}$: co − integration

The test is performed in levels and not in differences. The reason for performing the test with the variables in levels is because if the test was conducted with variables in differences, then there will never be any co-integrated relationship. Differencing makes all variables stationary. The Johansen test, states that if the Null is accepted then there are no co-integration relationships in the model and therefore the VAR model should be the appropriate model to be used. However, if the test fails to reject the Null hypothesis of no co-integration in the model, this means that the model contains one or more co-integrated relationships and the VECM model should be used.

The VECM model estimates both the short run and long run models. The two tests undertaken under the Johansen co-integration test are the Trace and Maximum Eigen value tests. These tests can be found in the appendix, in Table A29 for Bitcoin, Table B29 for Ethereum and table C29 for Ripple.

The VECM and VAR models will treat each variable as the dependent one each time. Therefore, the result will be seven different equations, each time treating another variable as the dependent variable. Even though we will estimate the effect of all the seven variables, we will concentrate on the effect of cryptocurrency price. This means that we are going to focus on the equation that treats price of each cryptocurrency as the dependent variable, equation 3 introduced earlier. This is the most important regression model for this paper.

The distinction between the VECM short run and long run models is mainly how the variables are treated. The short run VECM model, is a period of time in which one of the variables is kept fixed while the rest are varied, however, the VECM long run model, is a period of time in which all the variables are varied. In our case, since we would like to know how the prices are determined in real life situations when all variables are changing over time, it is important to take into consideration the long run VECM results.

7. Data and results:

7.1 Bitcoin Results:

VAR model:

The results of the VAR and VECM for Bitcoin are summarized in Table 6 at 5% significance level. In table A33 in the appendix we have the results in detail for the Vector Autoregression for Bitcoin.

Table 6 – Bitcoin results

Variables (lags)	**Short run VAR**	**Short run VECM**	**Long run VECM**
BTC price	(+)	(+)	
Inflation rate			
Volume of transactions			
Velocity			
Circulating Supply	(-)	Just rejected	(-)
Investment Attractiveness			
Macroeconomic/Financial indicators			

Starting with the VAR results, we observe that previous Bitcoin price has a significant positive effect on current Bitcoin price in the short run with a coefficient of 0.2665364. This means that an increase in the previous price of Bitcoin will lead to an increase in current price of Bitcoin.

Then, the next significant variable when treating price of Bitcoin as the dependent variable is the lag value of circulating supply. The lag value of circulating supply tends to affect negatively the price of Bitcoin in the current period in the short run. This means that the higher the circulating supply in the previous period will lead to lower current price of Bitcoin.

The next test performed is the Granger Causality test to examine whether the lag value of one variable helps predict the other variables in the model. The Null hypothesis is:

$$H_0: x \text{ does not Granger cause } y$$

$$H_1: x \text{ does Granger cause } y$$

As we can observe from table A36 in the appendix, circulating supply can help predict future price due to the reason that we reject the Null at 5% significance level. This confirms what we already predicted in the VAR model. It is important to note that the Granger causality test does not include the effect of the past values of the dependent variable on itself. For example, we have assumed that previous Bitcoin price is positively affecting current Bitcoin price. However, this effect is not shown in the Granger Causality test even though it is present in the VAR model.

Therefore, we can conclude that previous Bitcoin price can affect positively the current price and previous circulating supply can negatively affect Bitcoin price according to the short run VAR model.

VECM model:

Table A37 and A38 in the appendix estimate in detail the VECM short run and long run models correspondingly.

Short run:

Continuing with the VECM short run model and concentrating on having price as the dependent variable, we can confirm that the lagged value of price of Bitcoin positively affects the current price of Bitcoin in the short run, agreeing with the VAR results. The only difference here is that the effect of circulating supply is just rejected with the p-value being slightly higher than the 5% significance level. Therefore, the only difference in the short run VECM model and the VAR model is the fact that circulating supply does not seem to affect Bitcoin price.

Long run:

Continuing, we estimate the long run relationship of the variables, bearing in mind that the signs of the variables must be reversed. The restriction is placed on Bitcoin price which is indicated as the target variable. Not all long run variables indicated by the VECM model are shown to be significant. The only significant effect on Bitcoin price in the long run comes from the circulating supply indicator. The long run VECM model estimates a negative relationship between the two, keeping in mind the reversed signs.

This means that the higher Bitcoin circulating supply is, the lower the Bitcoin price due to the supply and demand behavior. This result matches with the VAR model, even though the short run VECM model was just rejecting the Null with the p-value being slightly above 5%. It is also important here to note that the long run VECM model will not show if the previous value of the dependent variable which is Bitcoin price will affect current Bitcoin price. In order to be precise with our results we will confirm the effect only in the short run.

Therefore, we can conclude that indeed circulating supply can be an important indicator in the short run and long run when trying to observe the price behavior of Bitcoin while previous Bitcoin prices can only affect current Bitcoin prices in the short run.

7.2 Ethereum results:

VAR model:

The results of the VAR and VECM for Ethereum are summarized in Table 7 at 5% significance level. The VAR model is also shown in detail in the apendix in table B31.

Table 7 – Ethereum results

Variables (lags)	**Short run VAR**	**Short run VECM**	**Long run VECM**
ETH price	(+)	(+)	
Inflation rate			(+)
Volume of transactions			
Velocity	(+)	(+)	(+)
Circulating Supply			
Investment Attractiveness	(-)	(-)	(-)
Macroeconomic/Financial indicators			

Going through the VAR results, when treating the price of Ethereum as the dependent variable, we observe a significant effect from previous Ethereum price levels. This means that past Ethereum price will lead to an upward pressure in current Ethereum price. Also, there is a significance positive relationship between the lag level of velocity and current Ethereum price. Lastly, there is a significant negative effect from the lag value of google search intensity on current Ethereum price, meaning that people that were using the search engine feature affected Ethereum price negatively by selling their coins. For this variable the direction could be either positive or negative depending on which effect is dominant.

The next test performed is the Granger Causality test to examine whether the variables are causing the dependent variable, which is Ethereum price but without taking into account the effect of its own previous value. The Granger Causality test shows that velocity and google search intensity can help predict the future price of Ethereum which is what we have estimated previously with the VAR model. These results are shown in table B35.

VECM model:

Table B36 and B37 in the appendix estimate in detail the VECM short run and long run models correspondingly.

Short run

Starting with the short run VECM model, and starting with Ethereum price as the dependent variable which is what interests us the most, we can confirm that previous Ethereum price and previous velocity levels will affect current Ethereum price positively, while previous search intensity levels will affect it negatively. The results are aligned with the ones found in the VAR model.

Long run:

For instance, we continue with the long run VECM model, bearing in mind that the signs of the variables are being reversed. Velocity level tends to affect positively Ethereum price in the long run. And lastly, the indicator associated with google search intensity can also have a positive or negative sign in the long run, but our long run analysis shows that there is a significant negative relationship. The majority of google searches with using the keyword "Ethereum" have led to negative impact in the Ethereum network and thus price. The VECM long run hypothesis estimated correctly the direction of all variables based on our assumptions. However, in the long run VECM model, we observe an additional significant variable that comes from the lag value of inflation rate and positively affect Ethereum price.

Concluding with the Ethereum results, in the short run Ethereum price is positively affected by previous Ethereum prices and previous velocity levels according to VAR and VECM short run models. However, in the long run we have an additional indicator that is significant and comes from the inflationary level. Specifically in the long run past inflationary levels tend to negatively affect the current price of Ethereum.

7.3 Ripple: results

VAR model:

The results of the VAR and VECM for Ripple are summarized in Table 8 at 5% significance level. We can also see the VAR model in detail in the appendix, table C31.

Table 8 – Ripple results:

Variables (lags)	**Short run VAR**	**Short run VECM**	**Long run VECM**
ETH price			
Inflation rate			
Volume of transactions			
Velocity		(-)	(-)
Circulating Supply		(-)	(-)
Investment Attractiveness		(+)	
Macroeconomic/Financial indicators			

Starting with the short run VAR model, we do not observe any significant result. This observation will be crucial since the VAR model suggests that the Ripple price is not affected by any of the variables in the short run. Since there is co-integration in our variables, using the VAR model may lead to loss of information. The solution in this case is to completely rely on the VECM model.

The Granger Causality test is performed in table C35 to investigate if the variables can actually help predict the direction of the rest of the variables. For Ripple price, we observe that no variable can help predict the value of current price which follows what we have found in the VAR model earlier.

VECM model

Table C36 and C37 in the appendix estimate in detail the VECM short run and long run models correspondingly. We choose to rely on the VECM model since there appears to be co-integration in Ripple variables.

Short run:

It is important here to state that the results shown in the VECM short run model differ with the VAR results. We observe that Ripple price is affected negatively by the lagged value of velocity level and by previous levels of circulating supply and positively by the lag level of google search intensity.

Long run:

We need to confirm the predictability of the variables by estimating the long run effect as well. Starting with the first variable which is shown to be significant in the long run VECM model which is the velocity level. This negative effect was also indicated by the short run VECM model. Moreover, continuing with the negative effect of circulating supply on Ripple price which was also one of the significant results of the short run VECM model.

We can confirm the validity of the VECM model by estimating a significant negative effect for the velocity level and circulating supply in the short run and long run. However, the variable representing the macroeconomic and financial indicators, google search intensity is not significant in the VECM long run model and is only significant in the short run.

8. Discussion:

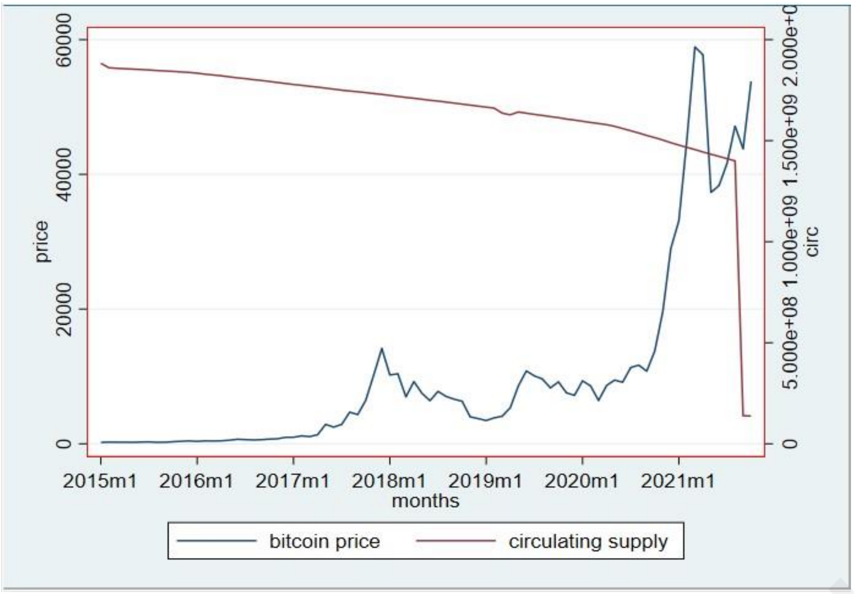
Bitcoin:

This section provides a description of the data and results. The graphical representations outlined in this section will only include the variables that appeared to be significant in the short run and long run, meaning both in VAR and VECM results. It is important to note that we exclude the effect of the dependent variable, cryptocurrency price, on itself.

We can conclude that there is a positive correlation between previous Bitcoin prices and current Bitcoin prices supported by the short run VAR and VECM models, and we can also conclude that circulating supply can have a negative effect on Bitcoin price due to the reason that VAR and long run VECM support this result.

We can see from graph 7 both Bitcoin price and the lag level of circulating supply are moving in opposite directions as predicted. We observe that during the early years, in 2015, Bitcoin circulation was high. Creators of the coin have produced 21 million of coins to be supplied in the market. As soon as people started buying the coin, we can see that supply was going down while price was going up. In 2021, there is a surge in Bitcoin price making supply so limited. Circulating supply is an important variable here, due to the reason that we already know that Bitcoin is capped at 21 million. Therefore, as soon as circulating supply goes down, we expect prices to go up in order to prevent the abundance of coins.

Graph 7 –Bitcoin Price & Circulating supply



This is a graph showing the negative relationship between the lagged value of circulating supply and Bitcoin price. Monthly data is used from January 2015 until October 2021. Bitcoin price is indicated on the vertical left axis in US dollars while lagged circulating supply is indicated on the vertical right axis. On the horizontal axis we have the monthly time frame.

Ethereum

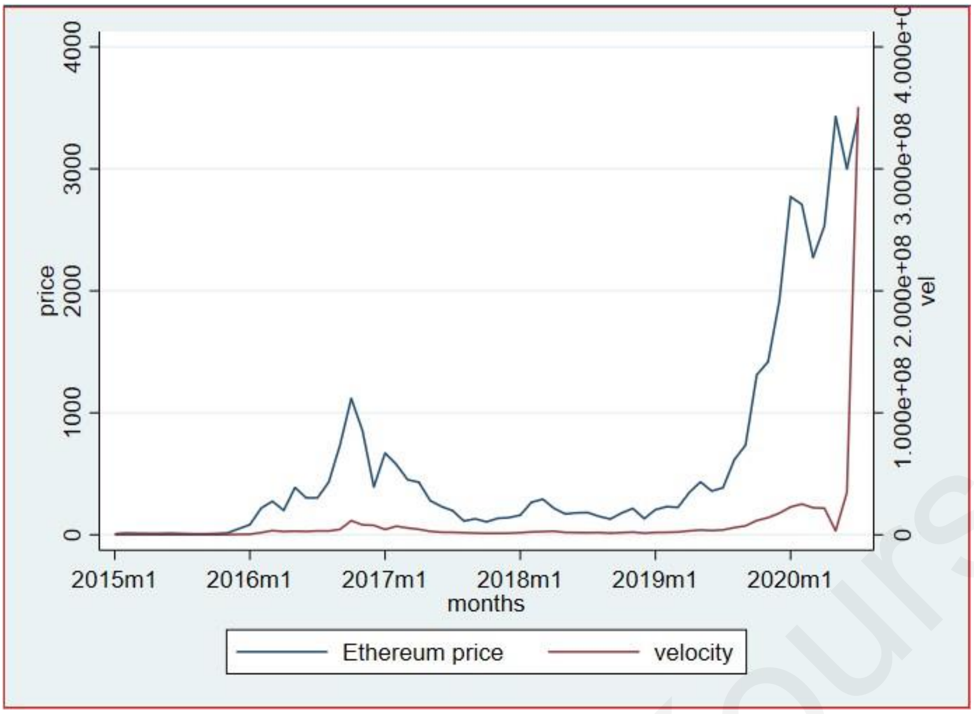
Continuing with the explanation of Ethereum results, we find some differences when compared to Bitcoin.

We have found a positive short run correlation between lagged price of Ethereum and current price of Ethereum. This positive relationship can be also explained by the positive performance Ethereum was experiencing in the cryptocurrency market.

Moreover, the relationship between lagged velocity and Ethereum price is estimated to be positive in the short run and long run. High velocity levels in the past meant that people were selling their Etereum coins for dollars. This led to low Ethereum prices in that period. But in the current period this low price attracted users to buy Ethereum coins and push the price upwards. Thus the positive relationship.

In general, cryptocurrencies like Ethereum are considered investment assets, therefore are expected to have low velocity levels. People prefer to buy the coins and keep them for long periods of time, having expectations that the price will go even higher. Below, we can see the graph describing the positive correlation between Ethereum price and the lag level of velocity which was found to be significant, both in the short run and long run. We can observe that velocity level follows a similar pattern with Ethereum price.

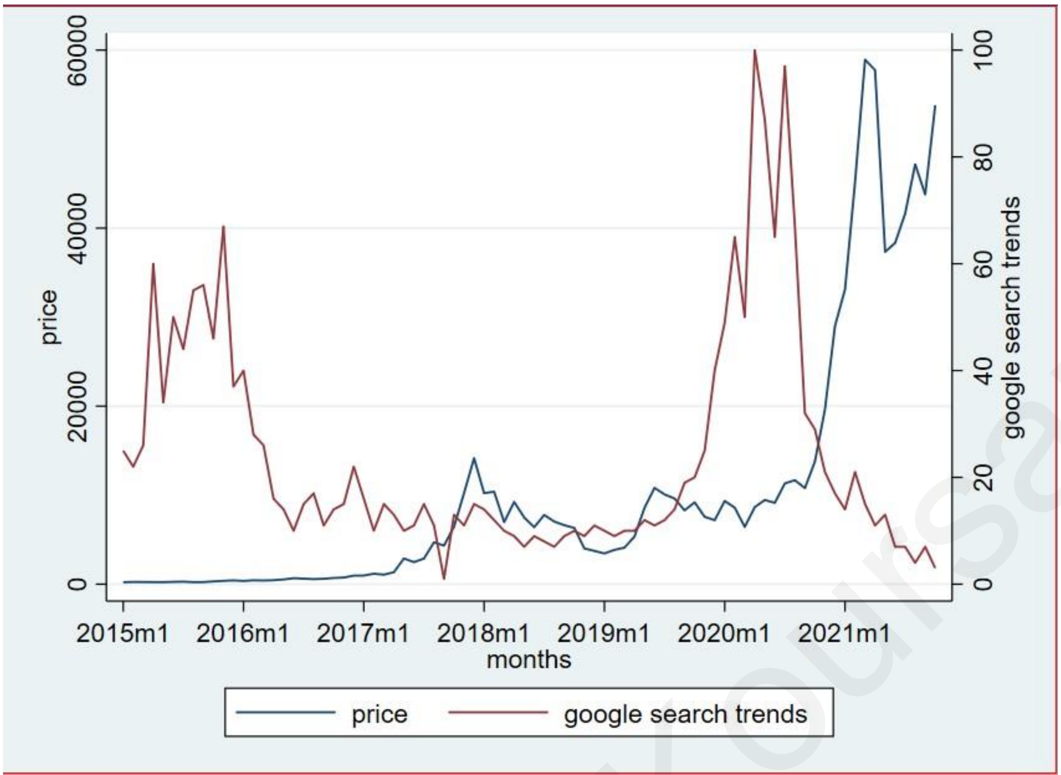
Graph 8 –Ethereum Price & Velocity



This is a graph showing the positive relationship between the lagged value of velocity and Ethereum price. Monthly data is used from January 2015 until October 2021. Ethereum price is indicated on the vertical left axis in US dollars while lagged velocity is indicated on the vertical right axis. On the horizontal axis we have the monthly time frame. All data is obtained from CoinMarketCap.

Lastly, the VAR and VECM model has estimated a negative relationship between past google search trends and current Ethereum price. This variable could have a positive or negative effect on Ethereum price. In our case, when google search intensity went up this meant that current price of Ethereum was going down. The reason of this effect may be due to the fact that it was experiencing some crashes during its lifecycle especially during 2017 and early 2021. Therefore, users who were using the google search tool to find more information were often discouraged due to the bad news and updates. Ethereum is considered to be one of the volatile cryptocurrencies and this sometimes discourages individuals from investing in that coin. In the graph below, we can observe that past Google search trends negatively affecting Ethereum price. Therefore, the majority of events and news that were posted in the social media platforms have led to uncertainty over the Ethereum network and led to higher selling power.

Graph 9 –Etherem Price & Google search trends



This is a graph showing the negative relationship between the lagged value of google search trends and Ethereum price. Monthly data is used from January 2015 until October 2021. Ethereum price is indicated on the vertical left axis in US dollars while lagged value of google search trends is indicated on the vertical right axis. On the horizontal axis we have the monthly time frame. All data is obtained from CoinMarketCap.

In the long run there is an additional variable that seems to be significant. This variable is the variable representing the inflation rate. High inflation in the economy means that traditional currency is depreciating and individuals are investing in cryptocurrencies with the expectation that their value will increase at a higher rate than the inflation rate. This is because during periods of financial instabilities or political corruptions there appears to be high uncertainty among individuals. This lack of trust in central authorities makes individuals to turn to safer assets such as the cryptocurrency network. This explains the positive relationship between the two. However, it is present only in the long run.

Ripple

The interesting results with Ripple are that when using the VAR model, we could not estimate any significant effect. In this case, we might question the reliability of the VAR model. When using the VAR model for time series data, there is a chance that there will be a loss of information, especially when having co- integrated relationships in the model. One solution will be to use differences in order to make the variables stationary but with the loss of ignoring any relationship between variables in levels. Therefore, the correct approach is to rely on the VECM model as we have found that co-integration exists in the model.

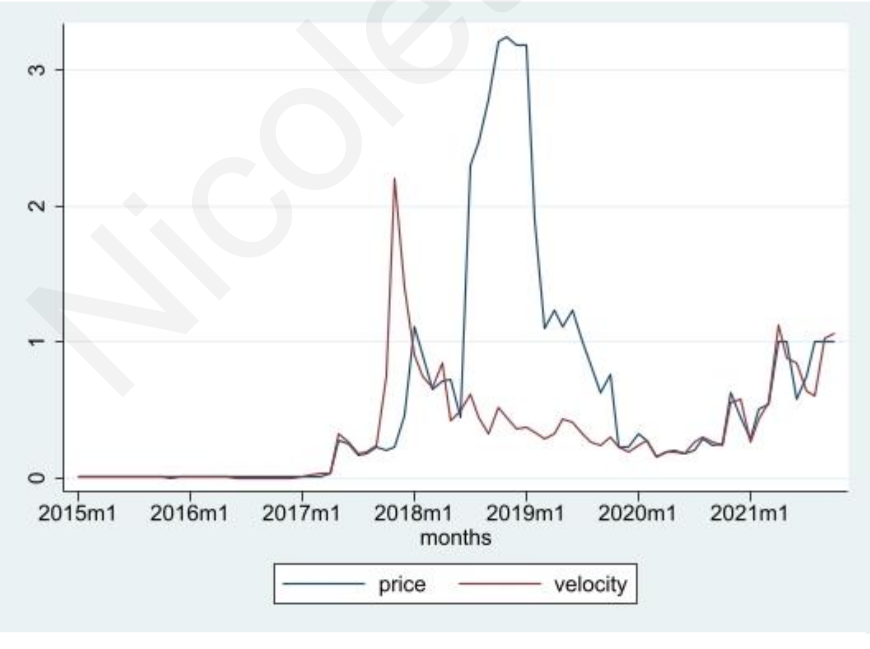
The VECM model has the advantage of combining both variables in levels and in differences. In this case, we can rely on VECM short run and long run results, as they appear to outperform the VAR model.

Therefore, continuing with the VECM short run and long run results, we estimated a negative relationship between the lagged level of velocity and current Ripple price. The difference here is the persistence effect. Higher past velocity levels, meant that people people were selling Ripple tokens to exchange them to dollars. This effect persisted until the current period. In the current period the high velocity will persist and the price of Ripple will go down as people are using Ripple to exchange to dollars. This is one of the characteristics of Ripple which confirms that it is used as a means of initiating transactions and thus has higher velocity compared to investment coins such as Bitcoin and Ethereum.

First of all, Ripple is a cryptocurrency created to act as a way of making transactions much faster and instant. This was the main reason that Ripple went into court in 2020, claiming that Ripple is not a currency but a security under the SEC (Securities and Exchange Commission). Ripple could be bought and sold instantly and easily due to its purpose. Ripple was not created to be considered as an asset but as a payment method. On the other hand, Ethereum can be considered an asset that its value is considered to increase over time. This also explains the opposing results found between Ehtereum and Ripple velocity levels. Therefore, from this we can quickly understand that velocity levels will be extremely high in general throughout Ripples' life cycle.

In graph 10 we can observe the negative relationship between Ripple price and past levels of velocity that persist over time.

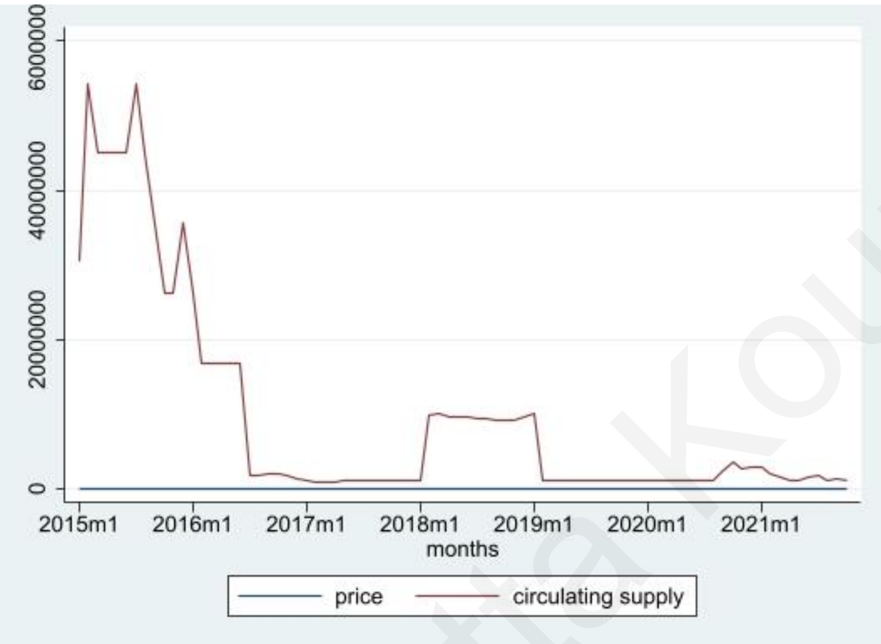
Graph 10 –Ripple Price & Velocity



This is a graph showing the negative relationship between the lagged value of velocity and Ripple price. Monthly data is used from January 2015 until October 2021. Ripple price is indicated on the vertical left axis in US dollars and shown by the dark blue line, while lagged velocity is shown by the red line. On the horizontal axis we have the monthly time frame. All

Moreover, the VECM short run and long run models estimated a negative relationship between past circulating supply and current Ripple price. This means that when past circulating supply is high then supply exceeds demand. This would have led to lower prices in the previous period and the persistent effect applies in this case as well. Therefore, Ripple price will continue to be low even in the current period. As we can see from graph 11, in 2015, circulating supply was at its highest and price at its lowest. As soon as transactions increased we can observe a contrasting pattern between the price and circulating supply.

Graph 11 –Ripple Price & Circulating supply



This is a graph showing the negative relationship between the lagged value of circulating supply and Ripple price. Monthly data is used from January 2015 until October 2021. Ripple price is shown by the dark blue line and it is clear that price was ranging approximately from $0-3 compared to the large number of circulating supply indicated on the left axis and shown by the red line. On the horizontal axis we have the monthly time frame. All data is obtained from CoinMarketCap.

The last significant effect estimated only by the VECM short run model is the positive effect between past google search intensity and current Ripple price. This meant that users were optimistic and willing to invest in Ripple when looking for updates on social media. A reason for that is that Ripple’s court case was progressing over time and the good news led to its attractiveness. However, this positive effect is significant only in the short run.

9. Conclusion

Bitcoin, Ethereum and Ripple were created for entirely different purposes. The diversity in my results for both short run and long run models confirm that prices react very differently. The paper relies on the use of both VAR and VECM models to determine how demand, supply, macroeconomic factors and investment attractiveness affect cryptocurrency prices. The empirical findings are important in terms of evaluating the price movements of cryptocurrencies, especially the ones I have included in my estimation. The additional variables as well as the comparison between the cryptocurrencies is something that very few or none of the previous studies took into consideration. Therefore, I believe this paper has contributed towards improving what was already known by previous analyses.

First of all, Bitcoin has a limited supply. From our results we can see that lagged circulating supply is significant as it adjusts to prevent the abundance of coins. This also applies to Ripple, which is also a coin that is finite in supply. However, Ethereum tokens are infinite and thus the reasoning behind the insignificant effect from the variable representing circulating supply.

Moreover, both Bitcoin and Ethereum are considered to be investment coins. The choice between investing in the two, relies greatly on peoples' decision making. However, Ripple is a coin which was discovered to act as a means of initiating transactions and not as a coin to invest in. This can be clearly shown by my results. We have estimated a positive relationship between the lagged velocity level and Ethereum price, contrasting with the negative relationship between the lagged velocity and Ripple price. This positive effect on Ethereum price, shows that in times of low velocity, people are buying Ethereum coins and this causes an increase in price. In the current period, price is high and this causes individuals to sell their coins. Thus we expect a decrease in price. Therefore, we have a positive relationship between past velocity levels and current Ethereum price which is what we expect.

However, with Ripple price we observe the exact opposite result, since Ripple is considered a coin which people use to transact faster. Thus we expect Ripple to have high velocity and persist over time. This is what we observe from our results since we estimated a negative effect from past velocity levels on price.

Moreover, another effect that shows that Ethereum is an investment coin, is the hedging behavior we observe. We have estimated a positive relationship between past inflation rates and current price. Higher inflation means that people are investing in coisn such as Ethereum to prevent the loss of value of their traditional currency. This causes higher prices in the Ethereum market and thus the positive relationship. This hedging behaviour is absent in Ripple, since Ripple is used for buying and selling instead of investment purposes.

All variables played a key role in the VAR and VECM models, however, the two variables that seem to be insignificant throughout all the estimations were the size of the cryptocurrency economy captured by the volume of transactions and the macroeconomic and financial indicators captured by the dow jones index. The size of the cryptocurrency economy may not be a factor that actually affects price, and a better indicator for this could be the circulating supply which is what was already included in the model. Moreover, the stock price index did not play a role in determining cryptocurrency prices since few companies are related to cryptocurrencies or use them as a source of payment at least for now. However, in the future we may observe more and more companies adopting cryptocurrencies as a payment system. Therefore, we may need to re-evaluate our conclusions, since cryptocurrencies are still evolving and new coins are being developed day by day.

10. References

Bajpai P., Rasure E. & Munichiello K. (2021) *How to invest in Bitcoin futures* (online) Available at: https://www.investopedia.com/articles/investing/012215/how-invest-bitcoin-exchange-futures.asp (Accessed 28 October 2021)

Balasubramaniam K. (2021) *Who sets the price of Commodities?* (online) Available at https://www.investopedia.com/ask/answers/06/commodityprices.asp (Accessed 18 October 2021)

Baur G. (2015) Bitcoin: *Medium of Exchange or Speculative Assets?* (online) Available at: Bitcoin: Medium of Exchange or Speculative Assets? (Accessed 7 October 2021)

Bohme R., Christin N. Benjamin E. & Moore T. (2015) Bitcoin: Economics, Technology and Governance (online) Available at: https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.29.2.213 (Accessed 22 October 2021)

Bojinov B. (2014) *Causes of Banking Crises in Modern world* (online) Available at https://www.researchgate.net/publication/272242386_Causes_of_Banking_Crises_in_Modern_World (Accessed 11 October 2021)

Bouoiyour A. & Selmi R. (2017) *The Bitcoin price formation: Beyond the fundamental sources* (online) Available at: NewpaperBitcoinJune2017.pdf (Accessed 5 October 2021)

Bouoiyour J. & Selmi R. (no date) The bitcoin price formation: Beyond thefundamental sources (online) Available at: https://arxiv.org/ftp/arxiv/papers/1707/1707.01284.pdf (Accessed 24 November 2021)

Brooks M. (2021) NationalWorld, *Why is Ripple XRP going up? What is the crypto asset, why are shares rising - and how to buy in the UK* (online) Available at: https://www.nationalworld.com/lifestyle/money/why-is-ripple-xrp-going-up-what-is-the-crypto-asset-why-are-shares-rising-and-how-to-buy-in-the-uk-3199214 (Accessed 13 April 2022)

Buchholz, M., J. Delaney, J. Warren, J. Parker (2012) *"Bits and Bets, Information, Price Volatility, and Demand for Bitcoin* (online) Available at: https://www.reed.edu/economics/parker/s12/312/finalproj/Bitcoin.pdf (Accessed 20 December 2021)

Cannon M. & Tuwiner J. (2021) *Is Bitcoin mining profitable or worth it in 2021?* (online) Available at: https://www.buybitcoinworldwide.com/mining/profitability (Accessed 6 October 2021)

Chambers C. (2020) *Bitcoin And Stocks' Correlation Reveal A Secret* (online) Available at: https://www.forbes.com/sites/investor/2020/05/13/bitcoin-and-stocks-correlation-reveal-a-secret/?sh=3c2221a512c2 (Accessed 8 October 2021)

Cheng H., Kaung Y. (2020) *The relationship between the economic policy uncertainty and the cryptocurrency market* (online) Available at: https://www.sciencedirect.com/science/article/abs/pii/S1544612319309596 (Accessed 17 October 2021)

Christopher A. Sims (2011) *Statistical modelling of monetary policy and its effects* (online) Available at: https://www.nobelprize.org/uploads/2018/06/sims_lecture.pdf (Accessed 5 October 2021)

Ciaian P. Kancs A. Rjcaniova M. (2018) *The price of Bitcoin: GARCH Evidence from high frequency data* (online) Available at: https://arxiv.org/pdf/1812.09452.pdf (Accessed 19 November 2021)

Ciaian P., Rajcaniova M. & Kancs A. (2015) *The economics of Bitcoin price formation* (online) Available at: https://www.tandfonline.com/doi/full/10.1080/00036846.2015.1109038?scroll=top&needAccess=true (Accessed 3 November 2021)

Coinbase (no date) *What is market cap* (online) Available at: https://www.coinbase.com/learn/crypto-basics/what-is-market-cap (Accessed 6 November 2021)

CoinMarketCap (2021) *Cryptocurrency Prices, Charts And Market Capitalizations | CoinMarketCap* (online) Available at https://coinmarketcap.com/ (Accessed 5 November 2021)

CoinMarketCap (no date) *Today's Cryptocurrency Prices by Market Cap (online) Available at:* https://coinmarketcap.com/ (Accessed 19 October 2021)

Conway L., Rasure E. & Clarine S. (2021) *Bitcoin Halving* (online) Available at: https://www.investopedia.com/bitcoin-halving-4843769 (Accessed 19 November 2021)

Cryptopedia (2021) *Key use cases of Ethereum and Blockchain* (online) Available at: https://www.gemini.com/cryptopedia/ethereum-smart-contracts-tokens-use-cases (Accessed 17 November 2021)

David L. Chaum (1981) *Untraceable Electronic Mail, Return Addresses and Digital Pseudonyms* (online) Available at: https://www.freehaven.net/anonbib/cache/chaum-mix.pdf (Accessed 15 October 2021)

Davis C. (2021) *Stablecoins* (online) Available at: https://www.benzinga.com/money/best-stablecoins-and-4-types-of-stablecoins/ (Accessed by 11 October 2021)

DeMatteo M. (2022), NextAdvisor: *Experts Predict How High Ethereum's Price Could Go in 2022, a 'Make-or-Break Year'* (online) Available at: https://time.com/nextadvisor/investing/cryptocurrency/ethereum-price-predictions/#:~:text=Coinpedia%20predicts%20an%20even%20higher,use%20Ethereum%20are%20notoriously%20high. (Accessed 13 April 2022)

Domm P. (2021) *Bitcoin and the stock market could trade more closely as the ctypto world expands* (online) Available at: https://www.cnbc.com/2021/04/20/bitcoin-stocks-could-become-more-correlated-as-crypto-adoption-grows.html (Accessed 7 October 2021)

Durant R. (2021) *Money velocity: Cryptocurrency valuation and inflation* (online) Available at: https://seekingalpha.com/article/4425445-money-velocity-cryptocurrency-valuation-and-inflation (Accessed 30 October 2021)

Dyhrberg A. (2016) *Hedging capabilities of bitcoin. Is it the virtual gold?* (online) Available at: https://econpapers.repec.org/article/eeefinlet/v_3a16_3ay_3a2016_3ai_3ac_3ap_3a139-144.htm (Accessed 7 November 2021)

Eisl A., Gasser S. Weinmayer K. (2015) *Does Bitcoin Improve Portfolio Diversification?* (online) Available at: SSRN-id2408997.pdf (Accessed 6 November 2021)

Finance yahoo (2021) *Yahoo is part of the Yahoo family of brands* (online) Available at https://finance.yahoo.com/u/yahoo-finance/watchlists/crypto-top-volume-24hr/ (Accessed 5 November 2021)

Floysd J. (2013) *Econometrics Basics: Avoiding Spurious Regression* (online) Available at: http://homes.chass.utoronto.ca/~floyd/spurreg.pdf (Accessed 5 October 2021)

Foelber D. (2021) *3 Reasons Why Bitcoin Is a Better Inflation Hedge Than Gold* , The Moltey Fool (online) Available at: https://www.fool.com/investing/2021/11/20/3-reasons-why-bitcoin-is-a-better-inflation-hedge/ (Accessed 15 April 2022)

Frankenfield J., Rasure E. & Munichiello K. (2021) *Ethereum Classic (ETC)* (online) Available at: https://www.investopedia.com/terms/e/ethereum-classic.asp (Accessed 19 October 2021)

Financial Times (2021) (online) Available at: https://accounts.ft.com/login?location=https%3A%2F%2Fwww.ft.com%2Fcontent%2Fb4925984-821c-45ef-91db-dadc1e30d1e2 (Accessed 6 October 2021)

Gaies B., Nakhil M., Sahut J. & Guesmi K. (2021) Is bitrac rooted in confidence?-Unraveling the determinants of globalized digital currencies (online) Available at: https://www.sciencedirect.com/science/article/abs/pii/S0040162521004704 (Accessed 25 October 2021)

Goddard J. (2021) *As global inflation heats up, Bitcoin Saves the day* (online) Available at: https://www.nasdaq.com/articles/as-global-inflation-heats-up-bitcoin-saves-the-day-2021-09-04 (Accessed 9 November 2021)

Google Trends (2021) Available at: https://trends.google.com/trends/explore?date=today%205-y&q=bitcoin (Accesses 10 October 2021)

Hayes A. (2017) *Cryptocurrency value formation: An empirical study leading to a cost of production model for valuating bitcoin* (online) Available at: https://www.sciencedirect.com/science/article/abs/pii/S0736585315301118 (Accessed 1 October 2021)
Hayes A. (2021) *What investors need to know about altcoins: Stablecoins* (online) Available at: https://www.investopedia.com/terms/s/stablecoin.asp (Accessed 21 October 2021)

Hern A. (2016) *Blockchain: the answer to life, the universe and everything?* (online) Available at: https://www.theguardian.com/world/2016/jul/07/blockchain-answer-life-universe-everything-bitcoin-technology (Accessed 22 October 2021)
Hinchliffe R. (2021*) What drives the value of crypto?* (online) Available at https://www.raconteur.net/finance/investing/what-drives-value-cryptocurrencies/ (Accessed 5 October 2021)

Insights (2020) *Bitcoin is a two part competition* (online) Available at: https://blog.chainalysis.com/reports/bitcoin-mining-markets-report (Accessed 7 November 2021)
Investing.com (no date) *EUR/USD - Euro US Dollar* (online) Available at: https://www.investing.com/currencies/eur-usd-historical-data (Accessed 5 November 2021)

Kristoufek L. (2013) Bitcoin meets Google trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era (online) Available at: https://www.nature.com/articles/srep03415?WT.ec_id=SREP-20131210 (Accessed 7 November 2021)

Kristoufek L. (2014) What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis (online) Available at: https://www.researchgate.net/publication/262805758_What_Are_the_Main_Drivers_of_the_Bitcoin_Price_Evidence_from_Wavelet_Coherence_Analysis (Accessed 6 May 2022)

Krugman P. (2013) *Bitcoin Is Evil* (online) Available at: https://krugman.blogs.nytimes.com/2013/12/28/bitcoin-is-evil/ (Accessed at 5 November 2021)

Kumar A. & Ajaz T. (2019) Co-movement in crypto-currency markets: evidences from wavelet analysis (online) Available at: https://jfin-swufe.springeropen.com/track/pdf/10.1186/s40854-019-0143-3.pdf (Accessed October 2021)

Layton R. (2021) *SEC Assault On Ripple Provokes Wider Debate* (online) Available at: https://www.forbes.com/sites/roslynlayton/2021/06/30/sec-assault-on-ripple-provokes-wider-debate/?sh=6c109f8529e1 (Accessed 21 November 2021)

Li X. & Wang A. (2017) The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin (online) Available at: https://www.sciencedirect.com/science/article/abs/pii/S0167923616302111 (Accessed 5 November 2021)

Leybourne S. and Newbold P. (1999) *The behavior of Dickey–Fuller and Phillips–Perron tests under the alternative hypothesis* (online) Available at: https://watermark.silverchair.com/ectj0092.pdf?token=AQECAHi208BE49Ooan9kkhW_Ercy7Dm3ZL_9Cf3qfKAc485ysgAAAtkwggLVBgkqhkiG9w0BBwagggLGMIICwgIBADCCArsGCSqGSIb3DQEHATAeBglghkgBZQMEAS4wEQQMYxo51Z-x0CBfQFqzAgEQgIICjHEnfhuPKR1RtZLOt6rDS0eJaNN_6K2f5EqHPPSbSlGybAe7_xmihpJqg_kDKITmMs2lrA76G0I3Bvlo9zOvx5BNjsTaHhXhT4ljdEYUcnfu3HlzR4Q48ADNTkEkfjbULdxiWxTAZ9UKl9_VrG5XSH2laIaye87E4INrsF9D2dpyQDIVNmXE-BJjx2UFbaW0tP25w1fSGQxj1eXcpOheG6Oxylqhn87IbnD0Sy3IyOBxfL8nTdH6V8nxTN4Weq1bYfpIfitZpkqF0qipIvZ4m-22lNQzMnMsN7Ih1Djek4_5beis4aa3ZcGPHrR7atEvg5APiWU6j72bO0ASrwNNhD7gMYEQV2OEYrkVD5jhTKPteqF3cHlm7JhJA2XaatFA4gYZO-dLFA410MypdwmElo_C-WH6N0r4m56SctY95y6H7PXY-wqTBVdmUNtGqjO3-4OLYwsxiOCTuNg_aqUKT8-v79c7QftfTOtnGwCl1ADPVVlNR2vTER0gP1STNAV3yL8_yufvLE4w-eLKUwfXFbK1aZROX0DhQrDD6-3j-uCNiZ8oIIy-UwAo4JXiULb9kkSXd3iYjkoxj6oxVhYnxciNe1_dhRuw4njcU8nCEYms2Ciohi-EJPiJUOpT3fY2LeyEWaIH7R6tE2UVUSudJHMDBvE3CB0AfpmRsAaPDhBcGVTGIzXTwRIFs4vDIhjqhZy5RXAethQTB4wiGJzVQTT-nDrRBvIfAGVD2YxxY_i3xb0qfNVOCn7cxirOXnEUZCW5Emk-rI6JmtP1M0P8t5KXLOO9IgC8UkYBvbjBo7Yx928rNExZYDD7365r6yr1XL5WBW7wy89WDCOi1I6hlXVpXBFbCe6DXH5wSY0 (Accessed 10 February 2022)

Li X. & Wang C. (2017) The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin (online) Available at: https://www.sciencedirect.com/science/article/abs/pii/S0167923616302111(Accessed 29 October 2021)

Lioudis N. (2021) *What is the Relationship between oil prices and inflation* (online) Available at: https://www.investopedia.com/ask/answers/06/oilpricesinflation.asp (Accessed 5 October 2021)

Liu M. & Yao Y. (2021) *Forecasting the price of Bitcoin using deep learning* (online) Available at: https://www.sciencedirect.com/science/article/abs/pii/S1544612320304864 (Accessed 11 October 2021)

Marr B. (no date) *Blockchain: A very short history of Ethereum Everyone should read* (online) Available at: https://bernardmarr.com/blockchain-a-very-short-history-of-ethereum-everyone-should-read/ (Accessed at 28 2021)

Marr B. (no date*) What is the difference between bitcoin and Ripple?* (online) Available at: https://bernardmarr.com/what-is-the-difference-between-bitcoin-and-ripple/(Accessed 1 November 2021)

Matta M., Lunesu I.M. & Mrchesi M. (2015) *Bitcoin Spread Prediction Using Social And Web Search Media* (online) Available at: https://www.researchgate.net/publication/279917417_Bitcoin_Spread_Prediction_Using_Social_And_Web_Search_Media#pf8 (Accessed 5 October 2021)

Mcmillan R. (2021) *The inside story of Mt. Gox Bitcoin's $460 Million Disaster* (online) Available at https://www.wired.com/2014/03/bitcoin-exchange/ (Accessed 5 October 2021)

Morse A. (2021) *Executive behind Facebook-backed Novi crypto wallet to leave company* (online) Available at: https://www.cnet.com/personal-finance/crypto/executive-behind-facebook-backed-novi-crypto-wallet-to-leave-company/ (Accessed 5 October 2021)

Nasdaq (2021) *As Global Inflation Heats Up, Bitcoin Saves The Day* (online) Available at https://www.nasdaq.com/articles/as-global-inflation-heats-up-bitcoin-saves-the-day-2021-09-04 (Accessed 4 December 2021)

Nasdaq (2021) *Bitcoin days destroyed* (online) Available at: https://data.nasdaq.com/data/BCHAIN/NTRAN-bitcoin-number-of-transactions (Accessed 1 November 2021)

Nasdaq (2021) *Bitcoin number of transactions* (online) Available at: https://data.nasdaq.com/data/BCHAIN/NTRAN-bitcoin-number-of-transactions (Accessed 1 November 2021)

Norland E. (2021) Reuters, *The Differences in Bitcoin and Ethereum Performance Drivers* (online), Available at: https://www.reuters.com/article/sponsored/bitcoin-ethereum-performance (Accessed 13 April 2022)

Panagiotidis T., Stegnos T. Vravosinos O. (2018) On the determinants of bitcoin returns: A LASSO approach (online) Available at: https://www.sciencedirect.com/science/article/abs/pii/S1544612318300023 (Accessed4 November 2021)

Parker J. (2012) *Bits and Bets, Information, price volatility and demand for Bitcoin* (online) Available at: https://www.reed.edu/economics/parker/s12/312/finalproj/Bitcoin.pdf (Accessed 7 October 2021)

Popper, N. (2015). *Digital gold: The untold story of Bitcoin* (online) Available at: https://www.ft.com/content/a493fe7e-03b5-11e5-b55e-00144feabdc0 (Accessed 9 November 2021)

Puterbaugh J. and Haar R. (2022), NextAdvisor: *Bitcoin Falls below $40,000 for the First Time in Almost a Month. Here's How Investors Should React* (online) Available at: https://time.com/nextadvisor/investing/cryptocurrency/bitcoin-crash-continues/ (Accessed 13 April 2022)

Radford M. (2014) *Horizon: The defenders of anonymity on the internet* (online) Available at: https://www.bbc.com/news/technology-29032399 (Accessed 9 October 2021)

Reif N., Clemon D. & Rathburn D. (2021) *How Blockchain can protect the global economy* (online) Available at: https://www.investopedia.com/tech/how-blockchain-can-protect-global-economy/ (Accessed 15 November 2021)

Renteria N. & Esposito A. (2021) *El Salvador world first adoption of bitcoin endures bumby first* day (online) Available at: https://www.reuters.com/business/finance/el-salvador-leads-world-into-cryptocurrency-bitcoin-legal-tender-2021-09-07/ (Accessed 9 November 2021)

River Financial (no date) *How Do Macroeconomic Events Affect Bitcoin?* (online) Available at: https://river.com/learn/how-do-macro-events-affect-bitcoin/ (Accessed 8 October 2021)

Roberts D. (2018) *Amid 2018 crypto crash, 3 kinds of believers come into focus* (online) Available at: https://finance.yahoo.com/news/amid-2018-crypto-crash-3-kinds-believers-come-focus-202424977.html (Accessed at 28 October 2021)

Roberts J. (202) *Ripple says it will be sued by the SEC, in what the company calls a parting shot at the crypto industry* (online) Available at: https://fortune.com/2020/12/21/ripple-to-be-sued-by-sec-cryptocurrency-xrp/ (Accessed 13 November 2021)

Royal J. & Voigt K. (2021) *What is cryptocurrency? What you should know?* (online) Available at: https://www.nerdwallet.com/article/investing/cryptocurrency-7-things-to-know (Accessed 3 November 2021)

SelfKey (2020) *A Comprehensive List of Cryptocurrency Exchange Hacks*, (online) Available at: https://selfkey.org/list-of-cryptocurrency-exchange-hacks/ (Accessed: 5 November 2021)

Sattarov O., Jeon H., Oh R. & Lee J. (2021) Forecasting Bitcoin Price Fluctuation by Twitter Sentiment Analysis (online) Available at: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9351527 (Accessed 29 December 2021)

Sharma R. (2020) Investopedia, *Coinbase to Suspend XRP Trading* (online) Available at: https://www.investopedia.com/coinbase-to-suspend-xrp-trading-5093844#:~:text=Key%20Takeaways,recent%20filing%20to%20go%20public. (Accessed 13 April 2022)

Shobhit S. & Rasure E. (2021) *What is a cryptocurrency public Ledger?* (online) Available at: https://www.investopedia.com/tech/what-cryptocurrency-public-ledger/ (Accessed 1 November 2021)

Smith C. (2018) Cryptocurrencies-An introduction to not so funny moneys(online) Available at: https://onlinelibrary.wiley.com/doi/full/10.1111/joes.12289 (Accessed 10 November 2021)

Sparkes M. (2021) *Why has El Salvador officially adopted bitcoin as its currency?* (online) Available at: https://www.newscientist.com/article/2289763-why-has-el-salvador-officially-adopted-bitcoin-as-its-currency/ (Accessed 10 November 2021)

Stephen J. & Newbold P. (1999) *The behavior of Dickey Fuller and Phillips-Perron tests under the alternative hypothesis* (online) Available at: https://www.jstor.org/stable/23114854?seq=14#metadata_info_tab_contents (Accessed 5 October 2021)

Teker D., Teer S. & Ozyesil (2019) *Determinants of cryptocurrency price movements* (online) Available at: http://heaig.org/images/proceedings_pdf/H1119510.pdf (Accessed 1 December 2021)

Teker D., Teker S. & Ozyesil M. (2020) *Macroeconomic Determinants of cryptocurrency volatility: Time series analysis* (online) Available at: http://jbepnet.com/journals/Vol_7_No_1_March_2020/8.pdf (Accessed 4 October 2021)

Weber E. (2015) *A Bitcoin Standard: Lessons from the Gold Standard* (online) Available at: https://www.bankofcanada.ca/wp-content/uploads/2015/12/bitcoin-standard-lessons.pdf (Accessed 19 November 2021)

XRP Ledger (no date) (online) Available at: https://xrpl.org/history.html (Accessed 19 November 2021)

Yahoo!Finance (no date) *Bitcoin USD (BTC-USD)* (online) Available at: https://finance.yahoo.com/u/yahoo-finance/watchlists/crypto-top-volume-24hr/ (Accessed 7 October 2021)

Yahoo!Finance (no date) *Top Cryptos by Volume (all currencies, 24hr*) (online) Available at: https://finance.yahoo.com/u/yahoo-finance/watchlists/crypto-top-volume-24hr/ (Accessed 7 October 2021)

Ycharts (2021) *Bitcoin Supply* (online) Available at: https://ycharts.com/indicators/bitcoin_supply (Accessed 6 November 2021)

11.Apendix: Specification Tests

11.1 Bitcoin

Tables A1-A7 estimate the Dickey Fuller tests for Bitcoin showing that velocity and number of transactions occurred in the Bitcoin network being the only stationary variables in levels.

Dickey Fuller Tests for Bitcoin

Table A1 - Bitcoin price

Dickey-Fuller test for unit root — Number of obs = 81
Variable: price — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	0.715	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.9901.

Table A2 – Price level index

Dickey-Fuller test for unit root — Number of obs = 81
Variable: eurusd — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-2.221	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.1986.

Table A3 – Level of transactions

Dickey-Fuller test for unit root — Number of obs = 81
Variable: trans — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-5.189	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A4 – Velocity level

Dickey-Fuller test for unit root — Number of obs = 81
Variable: velo — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-8.631	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A5 – Circulating Supply

Dickey-Fuller test for unit root — Number of obs = 81
Variable: circ — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	1.312	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.9967.

Table A6 – Stock level index

Dickey-Fuller test for unit root — Number of obs = 81
Variable: dowjones — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-1.346	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.6080.

Table A7 – Google search trends

Dickey-Fuller test for unit root — Number of obs = 81
Variable: wiki — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-2.502	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.1150.

The Phillips Perron tests are estimated in tables A8-A14 and we can confirm the stationarity results obtained by the Dickey Fuller tests.

Philips Perron tests for Bitcoin

Table A8 – Bitcoin price level

Phillips-Perron test for unit root — Number of obs = 81
Variable: price — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	1.508	-19.458	-13.548	-10.886
Z(t)	0.573	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.9869.

Table A9 – Price level index

Phillips-Perron test for unit root — Number of obs = 81
Variable: eurusd — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-9.653	-19.458	-13.548	-10.886
Z(t)	-2.227	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.1967.

Table A10 – Level of transactions

Phillips-Perron test for unit root — Number of obs = 81
Variable: trans — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-45.168	-19.458	-13.548	-10.886
Z(t)	-5.312	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A11 – Velocity level

Phillips-Perron test for unit root — Number of obs = 81
Variable: velo — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-77.820	-19.458	-13.548	-10.886
Z(t)	-8.628	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A12 – Circulating Supply

Phillips-Perron test for unit root — Number of obs = 81
Variable: circ — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	11.523	-19.458	-13.548	-10.886
Z(t)	2.265	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.9989.

Table A13 – Stock index

Phillips-Perron test for unit root — Number of obs = 81
Variable: dowjones — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-1.711	-19.458	-13.548	-10.886
Z(t)	-1.338	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.6117.

Table A14 – Google search trends

Phillips-Perron test for unit root — Number of obs = 81
Variable: wiki — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-11.758	-19.458	-13.548	-10.886
Z(t)	-2.441	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.1305.

The same tests are preformed but with the variables expressed in differences. The stationarity of the variables in differences is shown in tables A15-A21 for Dickey Fuller tests and in tables A21-A28 for Phillips Perron tests.

Dickey Fuller Tests for variables in differences

Table A15 – Bitcoin price level

Dickey-Fuller test for unit root Number of obs = 80
Variable: dprice Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-6.663	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A16 – Price level index

Dickey-Fuller test for unit root Number of obs = 80
Variable: deurusd Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-9.280	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A17 – Level of transactions

Dickey-Fuller test for unit root Number of obs = 80
Variable: dtrans Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-15.151	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A18 – Velocity level

Dickey-Fuller test for unit root Number of obs = 80
Variable: dvelo Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-15.214	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A19 – Circulating Supply

Dickey-Fuller test for unit root Number of obs = 80
Variable: dcirc Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-8.939	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A20 – Stock index

Dickey-Fuller test for unit root Number of obs = 80
Variable: ddowjones Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-7.085	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A21 – Google search trends

Dickey-Fuller test for unit root Number of obs = 80
Variable: dwiki Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-12.431	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Philips Perron Tests in Differences

Table A22 – Bitcoin price

Phillips-Perron test for unit root — Number of obs = 80
Variable: dprice — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-54.694	-19.440	-13.540	-10.880
Z(t)	-6.481	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A23 – Price level index

Phillips-Perron test for unit root — Number of obs = 80
Variable: deurusd — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-79.685	-19.440	-13.540	-10.880
Z(t)	-9.314	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A24 – Level of transactions

Phillips-Perron test for unit root — Number of obs = 80
Variable: dtrans — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-106.856	-19.440	-13.540	-10.880
Z(t)	-17.697	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A25 – Velocity level

Phillips-Perron test for unit root — Number of obs = 80
Variable: dvelo — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-104.353	-19.440	-13.540	-10.880
Z(t)	-18.822	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A26 – Circulating Supply

Phillips-Perron test for unit root — Number of obs = 80
Variable: dcirc — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-81.215	-19.440	-13.540	-10.880
Z(t)	-8.939	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A27 – Stock index

Phillips-Perron test for unit root — Number of obs = 80
Variable: ddowjones — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-57.441	-19.440	-13.540	-10.880
Z(t)	-6.984	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table A28 – Google search trends

Phillips-Perron test for unit root — Number of obs = 80
Variable: dwiki — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-114.773	-19.440	-13.540	-10.880
Z(t)	-12.078	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

The Johansen co-integration test is undertaken in order to see which model should be used in our analysis. It is divided to two parts, the Trace statistic test and the Maximum Rank test. As from table A29, which shows the Johansen co-integration test, it's evident that both the VAR and VECM models should be used in order to estimate the short and long run relationship, as there appears to be some co-integration relationship in the model.

Johansen Co-integration Test

Table A29

Johansen tests for cointegration

Trend: Constant — Number of obs = 80

Sample: 2015m3 thru 2021m10 — Number of lags = 2

Maximum rank	Params	LL	Eigenvalue	Trace statistic	Critical value 5%
0	56	-6609.9713	.	127.2459	124.24
1	69	-6588.232	0.41928	83.7671*	94.15
2	80	-6573.2385	0.31260	53.7803	68.52
3	89	-6563.0308	0.22523	33.3647	47.21
4	96	-6556.164	0.15774	19.6313	29.68
5	101	-6550.9076	0.12314	9.1184	15.41
6	104	-6548.2637	0.06396	3.8306	3.76
7	105	-6546.3484	0.04675		

Maximum rank	Params	LL	Eigenvalue	Eigenvalue Maximum	Critical value 5%
0	56	-6609.9713	.	49.4787	45.28
1	69	-6588.232	0.41928	29.9869	39.37
2	80	-6573.2385	0.31260	20.4156	33.46
3	89	-6563.0308	0.22523	13.7335	27.07
4	96	-6556.164	0.15774	10.5128	20.97
5	101	-6550.9076	0.12314	5.2879	14.07
6	104	-6548.2637	0.06396	3.8306	3.76
7	105	-6546.3484	0.04675		

* selected rank

Table A30 shows the number of lags to be used in the model. The criterion in order to determine the number of lags to be used in the model is based on the Final prediction error, Akaike, Hannan Quinn and Schwartz criteria. In this table there is a clear distinction that two out of four criteria support the use of zero lags and two out of the four criteria support the use of one lag.

Lag length criterion

Lag-order selection criteria

Sample: 2015m4 thru 2021m10 — Number of obs = 79

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-6579.96				6.2e+63	166.758	166.843*	166.968*
1	-6526.57	106.77	49	0.000	5.6e+63*	166.647*	167.32	168.327
2	-6489.28	74.591*	49	0.011	7.8e+63	166.944	168.205	170.093

* optimal lag

Endogenous: dprice deurusd dtrans dvel dcirc ddowjones dwiki

Exogenous: _cons

Table A30

However, stability condition needs to be satisfied in order to proceed with the VAR estimation and with the use of 0 lags. Unfortunately the VAR model will not satisfy the stability condition, indicated in table 31.

Stability condition with 0 lags

Table A31

Eigenvalue stability condition

Eigenvalue	Modulus
1.866866	1.86687
-1.538144	1.53814
-.5697997 + .6198314*i*	.84194
-.5697997 - .6198314*i*	.84194
.07950575 + .6079749*i*	.613151
.07950575 - .6079749*i*	.613151
-.00477909 + .4896397*i*	.489663
-.00477909 - .4896397*i*	.489663
.3086556 + .366296*i*	.479
.3086556 - .366296*i*	.479
-.3063197 + .2603571*i*	.402017
-.3063197 - .2603571*i*	.402017
-.2096927 + .2414598*i*	.319803
-.2096927 - .2414598*i*	.319803

At least one eigenvalue is at least 1.0.
VAR does not satisfy stability condition.

Therefore in table A32 we perform the test for stability using 1 lag in order to ensure stability and prevent inefficient results. Stability condition with one lag is satisfied, therefore the VAR model is measured using 1 lag.

Stability conditions with 1 lag

Table A32

Eigenvalue stability condition

Eigenvalue	Modulus
-.4900339 + .1763759*i*	.520809
-.4900339 - .1763759*i*	.520809
.3818925	.381892
.2194934	.219493
-.1815202 + .06891825*i*	.194163
-.1815202 - .06891825*i*	.194163
-.07831641	.078316

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

Bitcoin VAR model with 1 lag:

Table A33

Vector autoregression

Sample: 2015m3 thru 2021m10		Number of obs	= 80
Log likelihood	= -6609.971	AIC	= 166.6493
FPE	= 5.62e+63	HQIC	= 167.3178
Det(Sigma_ml)	= 1.38e+63	SBIC	= 168.3167

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dprice	8	3676.75	0.1529	14.43691	0.0439
deurusd	8	229.888	0.0679	5.828993	0.5599
dtrans	8	84261.2	0.3087	35.71712	0.0000
dvel	8	6.7e+06	0.2998	34.25307	0.0000
dcirc	8	1.4e+08	0.0387	3.217021	0.8642
ddowjones	8	73387.4	0.0661	5.658977	0.5801
dwiki	8	11.6507	0.1830	17.92103	0.0123

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dprice						
dprice L1.	.2665364	.1089444	2.45	0.014	.0530094	.4800635
deurusd L1.	-.0192872	1.759951	-0.01	0.991	-3.468728	3.430154
dtrans L1.	4.04e-06	.0041164	0.00	0.999	-.0080639	.008072
dvel L1.	-.0000189	.0000517	-0.37	0.714	-.0001203	.0000824
dcirc L1.	-8.61e-06	2.86e-06	-3.01	0.003	-.0000142	-3.01e-06
ddowjones L1.	-.0032559	.005478	-0.59	0.552	-.0139926	.0074808
dwiki L1.	-6.543464	32.28121	-0.20	0.839	-69.81347	56.72654
_cons	268.6584	416.5069	0.65	0.519	-547.6801	1084.997

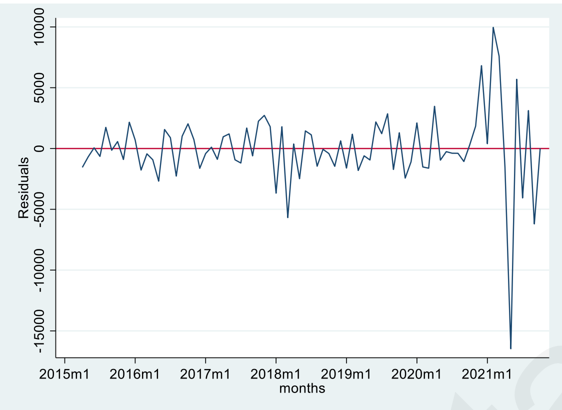
As we previously ensured stability condition, we also need to check for autocorrelation in residuals. In table A34 we can see that the mean value is really close to 0. Moreover, figure 1 is associated with the error term in order to verify and show that the residuals are close to the value of 0.

Generating error term

Table A34

Variable	Obs	Mean	Std. dev.	Min	Max
error	79	-6.41e-06	3131.335	-16467.16	9960.639

Figure 1



We also proceed with the Lagrange multiplier test for autocorrelation, with the Null hypothesis of no correlation at the selected lag. In table A35 we can confirm that there is no autocorrelation when using 1 lag, as the p-value is greater than 5% significance level, therefore we fail to reject the null of no correlation.

Lagrange multiplier test

Table A35

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	49.9200	49	0.43657
2	65.1492	49	0.06106

H0: no autocorrelation at lag order

The Granger Causality test examines whether the lag value of one variable helps predict the other variables in the model, shown in table A36

Granger causality test

Table A36

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
dprice	deurusd	.00012	1	0.991
dprice	dtrans	9.6e-07	1	0.999
dprice	dvel	.13416	1	0.714
dprice	dcirc	9.0731	1	0.003
dprice	ddowjones	.35326	1	0.552
dprice	dwiki	.04109	1	0.839
dprice	ALL	9.6171	6	0.142
deurusd	dprice	1.8529	1	0.173
deurusd	dtrans	1.85	1	0.174
deurusd	dvel	1.5689	1	0.210
deurusd	dcirc	.05079	1	0.822
deurusd	ddowjones	.61258	1	0.434
deurusd	dwiki	.16268	1	0.687
deurusd	ALL	5.628	6	0.466
dtrans	dprice	.34469	1	0.557
dtrans	deurusd	.1519	1	0.697
dtrans	dvel	4.5575	1	0.033
dtrans	dcirc	.19158	1	0.662
dtrans	ddowjones	.37239	1	0.542
dtrans	dwiki	1.574	1	0.210
dtrans	ALL	7.6164	6	0.268
dvel	dprice	.05504	1	0.815
dvel	deurusd	1.3455	1	0.246
dvel	dtrans	4.6431	1	0.031
dvel	dcirc	.47144	1	0.492
dvel	ddowjones	.17587	1	0.675
dvel	dwiki	.04708	1	0.828
dvel	ALL	6.2793	6	0.393
dcirc	dprice	2.0359	1	0.154
dcirc	deurusd	.00639	1	0.936
dcirc	dtrans	.81227	1	0.367
dcirc	dvel	.17905	1	0.672
dcirc	ddowjones	.00462	1	0.946
dcirc	dwiki	.09006	1	0.764
dcirc	ALL	3.2047	6	0.783
ddowjones	dprice	.27453	1	0.600
ddowjones	deurusd	.01889	1	0.891
ddowjones	dtrans	1.0283	1	0.311
ddowjones	dvel	.13385	1	0.714
ddowjones	dcirc	.14714	1	0.701
ddowjones	dwiki	.01889	1	0.891
ddowjones	ALL	1.6222	6	0.951
dwiki	dprice	.64072	1	0.423
dwiki	deurusd	6.0001	1	0.014
dwiki	dtrans	.92762	1	0.335
dwiki	dvel	6.0e-08	1	1.000
dwiki	dcirc	.59711	1	0.440
dwiki	ddowjones	.36067	1	0.548
dwiki	ALL	7.3021	6	0.294

Table A37 – VECM model (short run)

```
Sample: 2015m3 thru 2021m10                     Number of obs     =         80
                                                AIC               =   166.4308
Log likelihood = -6588.232                      HQIC              =   167.2545
Det(Sigma_ml)  =  8.01e+62                      SBIC              =   168.4853
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_price	9	3633.56	0.2088	18.74104	0.0275
D_eurusd	9	229.749	0.0824	6.378156	0.7016
D_trans	9	81075.3	0.3693	41.57264	0.0000
D_vel	9	5.6e+06	0.5212	77.28368	0.0000
D_circ	9	1.4e+08	0.0690	5.264503	0.8107
D_dowjones	9	73820.1	0.1367	11.24631	0.2592
D_wiki	9	11.7258	0.1842	16.03584	0.0661

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
D_price						
_ce1						
L1.	.0029684	.0017992	1.65	0.099	-.000558	.0064949
price						
LD.	.2596831	.1135644	2.29	0.022	.037101	.4822651
eurusd						
LD.	-.0217527	1.833358	-0.01	0.991	-3.615068	3.571562
trans						
LD.	-.0028386	.0046213	-0.61	0.539	-.0118961	.006219
vel						
LD.	-.0001041	.0000746	-1.40	0.163	-.0002503	.0000421
circ						
LD.	-6.21e-06	3.31e-06	-1.87	0.061	-.0000127	2.84e-07
dowjones						
LD.	-.0022642	.0057381	-0.39	0.693	-.0135106	.0089822
wiki						
LD.	-13.20765	33.86935	-0.39	0.697	-79.59036	53.17506
_cons	1143.305	685.0529	1.67	0.095	-199.3736	2485.984

Table A38 - VECM (long run)

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	6	51.37165	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
_ce1						
price	1	.	.	.	.	.
eurusd	86.2693	94.71559	0.91	0. 540	-99.36984	271.9085
trans	1.495208	.6369454	2.35	0. 771	.2468182	2.743599
vel	.0589783	.0086747	6.80	0.362	.0419763	.0759803
circ	.0008329	.0009115	-0.91	0.019	-.0026195	.0009536
dowjones	-.0332544	.1897709	-0.18	0.861	-.4051985	.3386897
wiki	2877.658	1729.927	1.66	0.096	-512.9359	6268.252
_cons	-526884.4	.	.	.	.	.

11.2 Ethereum

At first, the Dickey Fuller and the Perron tests are performed for all the variables in levels. Tables B1-B14estimate the Dickey Fuller tests and Perron tests for Ethereum variables in levels and the stationarity tests in differences are performed in tables B15-B28 to ensure stationarity for all the variables.

Dickey Fuller Tests for Ethereum

Table B1- Ethereum price

Dickey-Fuller test for unit root — Number of obs = 66
Variable: price — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	1.483	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.9975.

.

Table B2- Price level index

Dickey-Fuller test for unit root — Number of obs = 66
Variable: eurusd — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-1.851	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.3557.

Table B3 – Level of transactions

Dickey-Fuller test for unit root — Number of obs = 66
Variable: trans — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-0.526	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.8868.

Table B4 – Velocity level

Dickey-Fuller test for unit root — Number of obs = 66
Variable: liq — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	4.826	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 1.0000.

Table B5 – Circulating Supply

Dickey-Fuller test for unit root — Number of obs = 66
Variable: circ — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-4.970	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B6 – Stock level index

Dickey-Fuller test for unit root — Number of obs = 66
Variable: dowjones — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-0.981	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.7603.

Table B7 – Google search trends

Dickey-Fuller test for unit root — Number of obs = 66
Variable: wiki — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-2.644	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0842.

Philips Perron tests for Ethereum

Table B8 – Ethereum price level

Phillips-Perron test for unit root — Number of obs = 66
Variable: price — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	4.120	-19.188	-13.428	-10.796
Z(t)	2.047	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.9987.

Table B9 – Price level index

Phillips-Perron test for unit root — Number of obs = 66
Variable: eurusd — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-7.780	-19.188	-13.428	-10.796
Z(t)	-1.985	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.2930.

Table B10 – Level of transactions

Phillips-Perron test for unit root — Number of obs = 66
Variable: trans — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-1.196	-19.188	-13.428	-10.796
Z(t)	-0.528	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.8865.

Table B11 – Velocity level

Phillips-Perron test for unit root — Number of obs = 66
Variable: liq — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-114.606	-19.188	-13.428	-10.796
Z(t)	-2.532	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.1079.

Table B12 – Circulating Supply

Phillips-Perron test for unit root — Number of obs = 66
Variable: circ — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-1.295	-19.188	-13.428	-10.796
Z(t)	-8.169	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B13 – Stock index

Phillips-Perron test for unit root — Number of obs = 66
Variable: dowjones — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-1.514	-19.188	-13.428	-10.796
Z(t)	-0.989	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.7573.

Table B14 – Google search trends

Phillips-Perron test for unit root — Number of obs = 66
Variable: wiki — Newey-West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(rho)	-11.165	-19.188	-13.428	-10.796
Z(t)	-2.462	-3.558	-2.917	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.1251.

Dickey Fuller Tests for variables in differences

Table B15 – Ethereum price level

Dickey-Fuller test for unit root — Number of obs = 65
Variable: dprice — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-7.682	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B16 – Price level index

Dickey-Fuller test for unit root — Number of obs = 65
Variable: deurusd — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-7.482	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B17 – Level of transactions

Dickey-Fuller test for unit root — Number of obs = 65
Variable: dtrans — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-7.895	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B18 – Velocity level

Dickey-Fuller test for unit root — Number of obs = 65
Variable: dliq — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	7.615	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 1.0000.

Table B19 – Circulating Supply

Dickey-Fuller test for unit root — Number of obs = 65
Variable: dcirc — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-7.879	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B20 – Stock index

Dickey-Fuller test for unit root — Number of obs = 65
Variable: ddowjones — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-6.900	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B21 – Google search trends

Dickey-Fuller test for unit root — Number of obs = 65
Variable: dwiki — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-8.766	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Philips Perron Tests in Differences

Table B22 – Ethereum price

Phillips–Perron test for unit root   Number of obs = 65
Variable: dprice   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-63.443	-19.170	-13.420	-10.790
Z(t)	-7.676	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B23 – Price level index

Phillips–Perron test for unit root   Number of obs = 65
Variable: deurusd   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-57.327	-19.170	-13.420	-10.790
Z(t)	-7.471	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B24 – Level of transactions

Phillips–Perron test for unit root   Number of obs = 65
Variable: dtrans   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-63.105	-19.170	-13.420	-10.790
Z(t)	-7.893	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B25 – Velocity level

Phillips–Perron test for unit root   Number of obs = 65
Variable: dliq   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-208.953	-19.170	-13.420	-10.790
Z(t)	-3.951	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0017.

Table B26 – Circulating Supply

Phillips–Perron test for unit root   Number of obs = 65
Variable: dcirc   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-72.183	-19.170	-13.420	-10.790
Z(t)	-7.941	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B27 – Stock index

Phillips–Perron test for unit root   Number of obs = 65
Variable: ddowjones   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-46.607	-19.170	-13.420	-10.790
Z(t)	-6.859	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table B28 – Google search trends

Phillips–Perron test for unit root   Number of obs = 65
Variable: dwiki   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-60.908	-19.170	-13.420	-10.790
Z(t)	-9.103	-3.559	-2.918	-2.594

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Before deciding the model to be used, we proceed with the Johannsen co-integration test in order to test for the number of co-integrated relationships and decide whether to use VAR or VECM models. In table B29 we find evidence of more than one co-integrated relationship therefore we need to proceed with both the short run and long run models, VAR and VECM.

Table B29- Johannsen co-integration test

```
. vecrank price eurusd trans vel circ dowjones wiki, trend(constant) max

Johansen tests for cointegration
Trend: Constant                                  Number of obs  = 65
Sample: 2015m3 thru 2020m7                       Number of lags =  2
```

Maximum rank	Params	LL	Eigenvalue	Trace statistic	Critical value 5%
0	56	-5348.9502	.	248.2607	124.24
1	69	-5276.0696	0.89381	102.4996	94.15
2	80	-5255.75	0.46486	61.8603*	68.52
3	89	-5240.4426	0.37562	31.2455	47.21
4	96	-5232.9282	0.20643	16.2168	29.68
5	101	-5228.1164	0.13762	6.5931	15.41
6	104	-5224.8446	0.09577	0.0496	3.76
7	105	-5224.8198	0.00076		

Maximum rank	Params	LL	Eigenvalue	Eigenvalue Maximum	Critical value 5%
0	56	-5348.9502	.	145.7612	45.28
1	69	-5276.0696	0.89381	40.6393	39.37
2	80	-5255.75	0.46486	30.6148	33.46
3	89	-5240.4426	0.37562	15.0288	27.07
4	96	-5232.9282	0.20643	9.6237	20.97
5	101	-5228.1164	0.13762	6.5435	14.07
6	104	-5224.8446	0.09577	0.0496	3.76
7	105	-5224.8198	0.00076		

* selected rank

Table B30 shows that the appropriate lag length to be used in this model is one lag. Two out of four lag length criteria support the use of one lag instead of one criterion supporting the use of zero and two lags. So we proceed with estimating the VAR model using one lag

Lag length criterion

Table B30

Lag-order selection criteria

Sample: 2015m4 thru 2020m7   Number of obs = 64

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-5334.31				7.3e+63	166.916	167.009	167.152*
1	-5264.3	140.01	49	0.000	3.8e+63	166.259*	167.004*	168.148
2	-5206.67	115.27*	49	0.000	3.1e+63*	165.99	167.385	169.531

* optimal lag
Endogenous: dprice deurusd dtrans dvel dcirc ddowjones dwiki
Exogenous: _cons

Table B31 – Ethereum VAR model

Vector autoregression

Sample: 2015m3 thru 2020m7		Number of obs	= 65
Log likelihood =	-5348.95	AIC	= 166.3062
FPE =	4.00e+63	HQIC	= 167.0453
Det(Sigma_ml) =	7.08e+62	SBIC	= 168.1795

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dprice	8	199.628	0.3437	34.04633	0.0000
deurusd	8	201.864	0.1677	13.10133	0.0697
dtrans	8	1.5e+08	0.0344	2.312462	0.9405
dvel	8	2.6e+07	0.6036	98.97868	0.0000
dcirc	8	4.3e+07	0.0568	3.916616	0.7893
ddowjones	8	737.421	0.0721	5.050498	0.6538
dwiki	8	9.83965	0.3872	41.07384	0.0000

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dprice						
dprice						
L1.	.2703966	.1154813	2.34	0.019	.0440575	.4967358
deurusd						
L1.	.0025763	.1144378	0.02	0.982	-.2217177	.2268704
dtrans						
L1.	3.04e-07	1.67e-07	1.82	0.069	-2.34e-08	6.31e-07
dvel						
L1.	.0000282	5.55e-06	5.08	0.000	.0000173	.0000391
dcirc						
L1.	3.16e-07	5.90e-07	0.54	0.592	-8.41e-07	1.47e-06
ddowjones						
L1.	-.0117064	.0328261	-0.36	0.721	-.0760444	.0526316
dwiki						
L1.	-10.1425	2.301579	-4.41	0.000	-14.65351	-5.631484
_cons	6.205515	44.5157	0.14	0.889	-81.04365	93.45468

As the stability condition is met shown in table B32, we continue with the autocorrelation test.

Stability condition

Table B32

Eigenvalue stability condition

Eigenvalue	Modulus
6.244515	6.24451
.01210593 + .4842406i	.484392
.01210593 - .4842406i	.484392
.2429528 + .1043932i	.264431
.2429528 - .1043932i	.264431
-.2605424	.260542
-.01853267	.018533

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

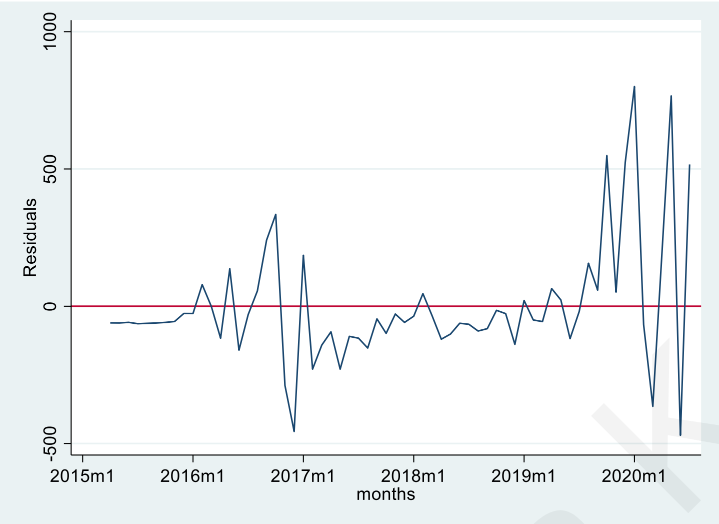
First by generating the mean value which is really close to 0 as shown in table B33 and then by showing it on the graph in figure 2 that shows that the error term is following the correct path.

Generating error term

Table B33

Variable	Obs	Mean	Std. dev.	Min	Max
error	64	3.35e-08	231.8752	-470.0013	800.1057

Figure 2



The Lagrange multiplier is performed next in table B34 accepting the Null hypothesis of no correlation. Specifically, for the use of one lag we observe that the p-value of the Lagrange multiplier test is higher than the 5% significance value and therefore we fail to reject the null of no correlation.

Lagrange multiplier test

Table B34

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	6.5415	1	0.8665
2	1.8665	1	0.17188

H0: no autocorrelation at lag order

Granger causality test

Table B35

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
dprice	deurusd	.00051	1	0.982
dprice	dtrans	3.312	1	0.069
dprice	dvel	25.818	1	0.000
dprice	dcirc	.28698	1	0.592
dprice	ddowjones	.12718	1	0.721
dprice	dwiki	19.419	1	0.000
dprice	ALL	34.034	6	0.000
deurusd	dprice	.69728	1	0.404
deurusd	dtrans	6.8958	1	0.009
deurusd	dvel	2.3455	1	0.126
deurusd	dcirc	2.2197	1	0.136
deurusd	ddowjones	2.5709	1	0.109
deurusd	dwiki	.04028	1	0.841
deurusd	ALL	12.606	6	0.050
dtrans	dprice	.60836	1	0.435
dtrans	deurusd	1.1326	1	0.287
dtrans	dvel	.16007	1	0.689
dtrans	dcirc	.06909	1	0.793
dtrans	ddowjones	.00499	1	0.944
dtrans	dwiki	.34568	1	0.557
dtrans	ALL	2.3106	6	0.889
dvel	dprice	.06737	1	0.795
dvel	deurusd	3.2064	1	0.073
dvel	dtrans	.15134	1	0.697
dvel	dcirc	1.494	1	0.222
dvel	ddowjones	.14354	1	0.705
dvel	dwiki	.58896	1	0.443
dvel	ALL	5.8351	6	0.442
dcirc	dprice	1.4816	1	0.224
dcirc	deurusd	.82674	1	0.363
dcirc	dtrans	.20828	1	0.648
dcirc	dvel	1.2559	1	0.262
dcirc	ddowjones	.1228	1	0.726
dcirc	dwiki	1.5209	1	0.217
dcirc	ALL	3.9166	6	0.688
ddowjones	dprice	1.4205	1	0.233
ddowjones	deurusd	.0029	1	0.957
ddowjones	dtrans	.13877	1	0.710
ddowjones	dvel	.3756	1	0.540
ddowjones	dcirc	.79281	1	0.373
ddowjones	dwiki	.23835	1	0.625
ddowjones	ALL	2.8269	6	0.830
dwiki	dprice	26.379	1	0.000
dwiki	deurusd	4.8516	1	0.028
dwiki	dtrans	1.2796	1	0.258
dwiki	dvel	.56614	1	0.452
dwiki	dcirc	2.7855	1	0.095
dwiki	ddowjones	1.3242	1	0.250
dwiki	ALL	39.728	6	0.000

VECM model (short run) - Table B36

Vector error-correction model

Sample: 2015m3 thru 2020m7		Number of obs =	65
		AIC =	164.4637
Log likelihood =	-5276.07	HQIC =	165.3744
Det(Sigma_ml) =	7.52e+61	SBIC =	166.7719

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_price	9	195.515	0.4121	39.25056	0.0000
D_eurusd	9	202.36	0.1793	12.23484	0.2004
D_trans	9	1.5e+08	0.0528	3.121973	0.9593
D_vel	9	9.0e+06	0.9554	1200.287	0.0000
D_circ	9	4.3e+07	0.6906	124.9685	0.0000
D_dowjones	9	743.945	0.1043	6.522075	0.6867
D_wiki	9	9.91466	0.3896	35.73905	0.0000

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
D_price						
_ce1						
L1.	-.1949524	.1053664	-1.85	0.064	-.4014667	.0115619
price						
LD.	.446813	.1538789	2.90	0.004	.1452159	.7484101
eurusd						
LD.	-.0306642	.121028	-0.25	0.800	-.2678748	.2065464
trans						
LD.	2.82e-07	1.75e-07	1.61	0.106	-6.05e-08	6.25e-07
vel						
LD.	.0000197	7.40e-06	2.66	0.008	5.17e-06	.0000342
circ						
LD.	1.54e-07	6.24e-07	0.25	0.805	-1.07e-06	1.38e-06
dowjones						
LD.	-.007865	.0343946	-0.23	0.819	-.0752772	.0595471
wiki						
LD.	-10.49694	2.414766	-4.35	0.000	-15.2298	-5.764091
_cons	-22.82332	49.13013	-0.46	0.642	-119.1166	73.46998

VECM (long run)

Table B37

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	6	2865.441	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
_ce1						
price	1	.	.	.	.	.
eurusd	-4.95e-09	.0339574	2.13	0.033	.0057144	.138825
trans	-.0001022	4.63e-08	-0.11	0.915	-9.57e-08	8.58e-08
vel	-.0022697	6.35e-06	-16.09	0.000	-.0001147	-.0000898
circ	1.37e-08	2.86e-08	0.48	0.631	-4.23e-08	6.98e-08
dowjones	.004479	.008302	0.54	0.590	-.0117927	.0207507
wiki	4.737321	1.824281	-2.60	0.009	-8.312846	-1.161795
_cons	-1238.714	.	.	.	.	.

11.3 Ripple:

The stationarity tests for Ripple variables, in tables C1-C14, where the Dickey Fuller and Phillips Perron tests are performed accordingly for the variables in levels. In order to ensure the stationarity of all the variables, we generate the variables in differences and perform the same stationarity tests, also shown in tables C15-21 and C22-C28.

Dickey Fuller Tests for Ripple

Table C1 - Ripple price

Dickey-Fuller test for unit root   Number of obs = 81
Variable: price   Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-1.577	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.4952.

Table C2 – Price level index

Dickey-Fuller test for unit root   Number of obs = 81
Variable: eurusd   Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-2.221	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.1986.

Table C3 – Level of transactions

Dickey-Fuller test for unit root   Number of obs = 81
Variable: trans   Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-5.359	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C4 – Velocity level

Dickey-Fuller test for unit root   Number of obs = 81
Variable: liq   Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-2.708	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0727.

Table C5 – Circulating Supply

Dickey-Fuller test for unit root   Number of obs = 81
Variable: circ   Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	0.626	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.9882.

Table C6 – Stock level index

Dickey-Fuller test for unit root   Number of obs = 81
Variable: dowjones   Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-1.556	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.5058.

Table C7 – Google search trends

Dickey-Fuller test for unit root   Number of obs = 81
Variable: wiki   Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-4.203	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0007.

Philips Perron tests

Table C8 – Ripple price level

Phillips–Perron test for unit root — Number of obs = 81
Variable: price — Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-4.886	-19.458	-13.548	-10.886
Z(t)	-1.257	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.6486.

Table C9 – Price level index

Phillips–Perron test for unit root — Number of obs = 81
Variable: eurusd — Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-9.653	-19.458	-13.548	-10.886
Z(t)	-2.227	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.1967.

Table C10 – Level of transactions

Phillips–Perron test for unit root — Number of obs = 81
Variable: trans — Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-41.301	-19.458	-13.548	-10.886
Z(t)	-5.300	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C11 – Velocity level

Dickey–Fuller test for unit root — Number of obs = 81
Variable: liq — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-2.708	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0727.

Table C12 – Circulating Supply

Dickey–Fuller test for unit root — Number of obs = 81
Variable: circ — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	0.626	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.9882.

Table C13 – Stock index

Dickey–Fuller test for unit root — Number of obs = 81
Variable: dowjones — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-1.556	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.5058.

Table C14 – Google search trends

Dickey–Fuller test for unit root — Number of obs = 81
Variable: wiki — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-4.203	-3.537	-2.905	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0007.

Dickey Fuller Tests for variables in differences

Table C15 – Ripple price level

Dickey-Fuller test for unit root — Number of obs = 80
Variable: dprice — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-9.097	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C16 – Price level index

Dickey-Fuller test for unit root — Number of obs = 80
Variable: deurusd — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-9.280	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C17 – Level of transactions

Dickey-Fuller test for unit root — Number of obs = 80
Variable: dtrans — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-12.323	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C18 – Velocity level

Dickey-Fuller test for unit root — Number of obs = 80
Variable: dliq — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-9.150	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C19 – Circulating Supply

Dickey-Fuller test for unit root — Number of obs = 80
Variable: dcirc — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-6.392	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C20 – Stock index

Dickey-Fuller test for unit root — Number of obs = 80
Variable: ddowjones — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-12.528	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C21 – Google search trends

Dickey-Fuller test for unit root — Number of obs = 80
Variable: dwiki — Number of lags = 0

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-12.610	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Philips Perron Tests in Differences

Table C22 – Ripple price

Phillips–Perron test for unit root   Number of obs = 80
Variable: dprice   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-68.215	-19.440	-13.540	-10.880
Z(t)	-9.350	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C23 – Price level index

Phillips–Perron test for unit root   Number of obs = 80
Variable: deurusd   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-79.685	-19.440	-13.540	-10.880
Z(t)	-9.314	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C24 – Level of transactions

Phillips–Perron test for unit root   Number of obs = 80
Variable: dtrans   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-87.447	-19.440	-13.540	-10.880
Z(t)	-14.508	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C25 – Velocity level

Phillips–Perron test for unit root   Number of obs = 80
Variable: dliq   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-68.746	-19.440	-13.540	-10.880
Z(t)	-9.413	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C26 – Circulating Supply

Phillips–Perron test for unit root   Number of obs = 80
Variable: dcirc   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-49.201	-19.440	-13.540	-10.880
Z(t)	-6.133	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C27 – Stock index

Phillips–Perron test for unit root   Number of obs = 80
Variable: ddowjones   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-97.525	-19.440	-13.540	-10.880
Z(t)	-13.304	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

Table C28 – Google search trends

Phillips–Perron test for unit root   Number of obs = 80
Variable: dwiki   Newey–West lags = 3

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(rho)	-88.462	-19.440	-13.540	-10.880
Z(t)	-15.193	-3.538	-2.906	-2.588

MacKinnon approximate *p*-value for Z(t) = 0.0000.

The Johansen co-integration test is performed in table C29. Both the VAR and VECM model should be estimated like previously done with Bitcoin and Ethereum models.

Johansen Co-integration Test

Table C29

Johansen tests for cointegration
Trend: Constant   Number of obs = 80
Sample: 2015m3 thru 2021m10   Number of lags = 2

Maximum rank	Params	LL	Eigenvalue	Trace statistic	Critical value 5%
0	56	-3374.5889	.	169.7659	124.24
1	69	-3341.9741	0.55752	104.5363	94.15
2	80	-3322.9923	0.37783	66.5728*	68.52
3	89	-3309.5646	0.28516	39.7172	47.21
4	96	-3298.933	0.23340	18.4541	29.68
5	101	-3293.3476	0.13032	7.2832	15.41
6	104	-3290.9301	0.05865	2.4483	3.76
7	105	-3289.706	0.03014		

Maximum rank	Params	LL	Eigenvalue	Eigenvalue Maximum	Critical value 5%
0	56	-3374.5889	.	65.2296	45.28
1	69	-3341.9741	0.55752	37.9636	39.37
2	80	-3322.9923	0.37783	26.8555	33.46
3	89	-3309.5646	0.28516	21.2632	27.07
4	96	-3298.933	0.23340	11.1709	20.97
5	101	-3293.3476	0.13032	4.8349	14.07
6	104	-3290.9301	0.05865	2.4483	3.76
7	105	-3289.706	0.03014		

* selected rank

Before proceeding with the VAR test, we estimate the appropriate lag length to be used in table C30. The appropriate lag length to be used is one lag supported by two criteria. Therefore, we continue the model with the lag length of 1, estimated in table C31.

Lag length criterion

Table C30

2 out of 4 criteria support the use of 1 lag

Lag-order selection criteria

Sample: 2015m4 thru 2021m10   Number of obs = 79

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-3427.83				1.4e+29	86.9578	87.0419	87.1677*
1	-3332.4	190.86	49	0.000	4.3e+28*	85.7823	86.4552*	87.4619
2	-3267.21	130.39*	49	0.000	2.9e+28	85.3723*	86.634	88.5215

* optimal lag
Endogenous: dprice deurusd dtrans dvel dcirc ddwojones dwiki
Exogenous: _cons

Ripple VAR model with 1 lag:

Table C31

Vector autoregression

Sample: 2015m3 thru 2021m10		Number of obs =	80
Log likelihood =	-3374.589	AIC =	85.76472
FPE =	4.19e+28	HQIC =	86.43324
Det(Sigma_ml) =	1.03e+28	SBIC =	87.43214

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dprice	8	.143555	0.0471	3.951663	0.7853
deurusd	8	232.288	0.0484	4.065021	0.7723
dtrans	8	370.848	0.5711	106.521	0.0000
dvel	8	.246056	0.0517	4.364694	0.7369
dcirc	8	4.0e+06	0.2383	25.03276	0.0007
ddowjones	8	1426.42	0.1377	12.77991	0.0777
dwiki	8	15.6003	0.3174	37.20108	0.0000

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
dprice						
dprice L1.	-.1147822	.1321368	-0.87	0.385	-.3737656	.1442012
deurusd L1.	-.0000583	.0000727	-0.80	0.423	-.0002009	.0000843
dtrans L1.	-.0000177	.0000293	-0.60	0.546	-.0000753	.0000398
dvel L1.	.0193208	.0642606	0.30	0.764	-.1066278	.1452693
dcirc L1.	-3.81e-10	3.88e-09	-0.10	0.922	-7.98e-09	7.22e-09
ddowjones L1.	-3.68e-07	.0000109	-0.03	0.973	-.0000218	.000021
dwiki L1.	.0018116	.0009903	1.83	0.067	-.0001293	.0037525
_cons	.0132897	.0156327	0.85	0.395	-.0173498	.0439292

Table C32 ensures that all variables are stable and the model satisfies the stability condition.

Stability conditions with 1 lag

Table C32

Eigenvalue stability condition

Eigenvalue	Modulus
-.07056544 + .3752412*i*	.381819
-.07056544 - .3752412*i*	.381819
-.2299144 + .2250134*i*	.321701
-.2299144 - .2250134*i*	.321701
-.1535279	.153528
-.05296776	.052968
.02300136	.023001

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

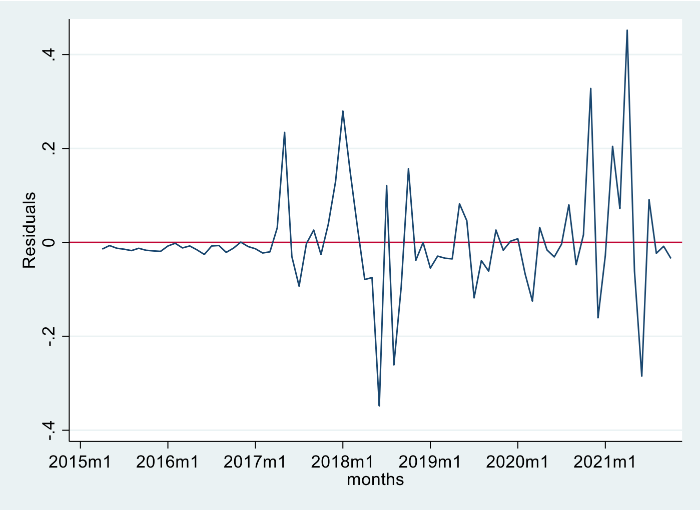
Next, the tests for autocorrelation are undertaken and table C33 estimates the mean value which is really close to zero as shown from the graph in figure 3.

Autocorelation: generating residual

Table C33

```
   Variable │        Obs        Mean    Std. dev.       Min        Ma
> x
────────────┼───────────────────────────────────────────────────────
> ─
      error │         79   -5.62e-10     .112666  -.3481335   .451865
> 8
```

Figure 3



The Lagrange multiplier test is performed to test for autocorrelation and ensures that we do not have autocorrelation at the chosen lag level indicated in Table C34, as the p-value is greater than 5% significance level, therefore we fail to reject the null of no correlation.

Lagrange multiplier test

Table C34

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	55.4248	49	0.24531
2	96.8775	49	0.00005

H0: no autocorrelation at lag order

Granger causality test

Table C35

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
dprice	deurusd	.64177	1	0.423
dprice	dtrans	.36524	1	0.546
dprice	dvel	.0904	1	0.764
dprice	dcirc	.00966	1	0.922
dprice	ddowjones	.00114	1	0.973
dprice	dwiki	3.3468	1	0.067
dprice	ALL	3.8782	6	0.693
deurusd	dprice	.21107	1	0.646
deurusd	dtrans	.27431	1	0.600
deurusd	dvel	.64957	1	0.420
deurusd	dcirc	1.1033	1	0.294
deurusd	ddowjones	1.1227	1	0.289
deurusd	dwiki	.22225	1	0.637
deurusd	ALL	3.8682	6	0.695
dtrans	dprice	1.0383	1	0.308
dtrans	deurusd	.18571	1	0.667
dtrans	dvel	.89348	1	0.345
dtrans	dcirc	.04182	1	0.838
dtrans	ddowjones	84.044	1	0.000
dtrans	dwiki	7.1e-05	1	0.993
dtrans	ALL	87.277	6	0.000
dvel	dprice	.13899	1	0.709
dvel	deurusd	1.3927	1	0.238
dvel	dtrans	.11332	1	0.736
dvel	dcirc	1.5724	1	0.210
dvel	ddowjones	.00435	1	0.947
dvel	dwiki	.10642	1	0.744
dvel	ALL	4.2588	6	0.642
dcirc	dprice	.0859	1	0.769
dcirc	deurusd	.40029	1	0.527
dcirc	dtrans	.08899	1	0.765
dcirc	dvel	1.7083	1	0.191
dcirc	ddowjones	.00395	1	0.950
dcirc	dwiki	13.097	1	0.000
dcirc	ALL	17.452	6	0.008
ddowjones	dprice	.50775	1	0.476
ddowjones	deurusd	.49943	1	0.480
ddowjones	dtrans	1.3321	1	0.248
ddowjones	dvel	.00011	1	0.992
ddowjones	dcirc	.01011	1	0.920
ddowjones	dwiki	.01967	1	0.888
ddowjones	ALL	2.3075	6	0.889
dwiki	dprice	.13229	1	0.716
dwiki	deurusd	.34745	1	0.556
dwiki	dtrans	.0758	1	0.783
dwiki	dvel	9.1674	1	0.002
dwiki	dcirc	15.692	1	0.000
dwiki	ddowjones	.08971	1	0.765
dwiki	ALL	23.5	6	0.001

VECM model (short run)

Table C36

Vector error-correction model

Sample: 2015m3 thru 2021m10		Number of obs	=	80
		AIC	=	85.27435
Log likelihood = -3341.974		HQIC	=	86.09806
Det(Sigma_ml) = 4.55e+27		SBIC	=	87.32885

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_price	9	.118593	0.3636	40.57342	0.0000
D_eurusd	9	226.541	0.1079	8.584938	0.4764
D_trans	9	372.638	0.5730	95.28696	0.0000
D_vel	9	.236536	0.1385	11.41395	0.2484
D_circ	9	3.9e+06	0.2794	27.53308	0.0011
D_dowjones	9	1426.96	0.1653	14.0587	0.1203
D_wiki	9	14.8293	0.3920	45.78058	0.0000

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
D_price						
_ce1 L1.	-.5563272	.0947165	-5.87	0.000	-.7419682	-.3706862
price LD.	.0792449	.1197132	0.66	0.508	-.1553886	.3138784
eurusd LD.	-.0000908	.0000636	-1.43	0.153	-.0002155	.0000338
trans LD.	-.0000149	.0000256	-0.58	0.560	-.000065	.0000352
vel LD.	-.2014093	.0674063	-2.99	0.003	-.3335231	-.0692955
circ LD.	-2.75e-08	5.71e-09	-4.81	0.000	-3.86e-08	-1.63e-08
dowjones LD.	1.41e-06	9.51e-06	0.15	0.882	-.0000172	.00002
wiki LD.	.0025793	.0008722	2.96	0.003	.0008699	.0042888
_cons	.0570624	.0155194	3.68	0.000	.0266449	.0874799

VECM model (long run)

Table C37

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	6	293.3407	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
_ce1						
price	1	.	.	.	.	.
eurusd	-9.98e-06	.0000543	-0.18	0.854	-.0001163	.0000964
trans	4.46e-06	.0000426	0.10	0.917	-.0000791	.000088
vel	.5117473	.0719282	-7.11	0.000	-.652724	-.3707706
circ	3.93e-08	9.21e-09	-4.27	0.000	-5.74e-08	-2.13e-08
dowjones	8.50e-06	4.00e-06	2.12	0.354	6.53e-07	.0000163
wiki	-.0014537	.0015562	-0.93	0.350	-.0045038	.0015964
_cons	-.0671391	.	.	.	.	.