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AN ANALYSIS OF CURRENT CRYPTO ASSET VALUATION APPROACHES IN THE CONTEXT OF BIG DATA

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ABSTRACT

The importance crypto assets have acquired throughout the last few years, both socially and economically, is undeniable. Since the market of crypto assets represents a potentially profitable investment opportunity, the focus of many investors lies in estimating their value. The main purpose of this research is to analyze and compare some of the most widespread crypto assets valuation approaches (using Bitcoin as an example) with a view to addressing their applicability. Having understood how Bitcoin is usually valued and how different factors may influence its value, a vector autoregression (VAR) predictive model is built with the aim of developing a potential model to estimate the value of Bitcoin. The review of current valuation methods reveals the lack of consensus regarding crypto assets' value drivers. However, the predictive model shows promising results and can thus be considered as a solid foundation for gaining deeper insights into the value drivers of crypto assets. This proves highly useful considering that this research concludes with the imperative need for investors to better comprehend where crypto assets' value stems from with a view to properly estimating the latter.

Key words: *crypto assets, bitcoin, valuation approach, digital currencies, value drivers, blockchain, VAR, predictive algorithm*

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GLOSSARY OF ACRONYMS AND ABBREVIATIONS

ACV: annual contract value

BTC: Bitcoin

BTC USD: Bitcoin price in USD

M: Crypto Asset Market Capitalization

NVHR: Network-Value-Hashrate

NVHRS: Network-Value-Hashrate Smooth

NVML: Network-Value-Metcalfe’s Law

NVMLS: Network-Value-Metcalfe’s Law Smooth

NVOL: Network-Value-Odlyzko’s Law

NVOL: Network-Value-Odlyzko’s Law Smooth

NVRV: Network-Value-Realized-Value

NVT: Network Value to Transactions

NVTS: Network Value to Transactions Smooth

P: On-chain Transaction Volume

Q: Number of transactions executed in the period analyzed

SF: Stock-to-Flow

TAM: Total Addressable Market

V: Velocity.

VAR: vector autoregression

1. INTRODUCTION. OBJECTIVES AND THEME JUSTIFICATION

The vast expansion of technology has definitely not gone unnoticed. Technological innovation has fueled such a rapid pace of change that every aspect of our lives has been altered, including the field of finance. Amongst the multiple disruptive events shaping the latter, the rise of crypto assets is of key interest for this investigation. With Bitcoin (BTC from now on) as the pacesetter, the market of crypto assets has grown at an astonishing pace and is fostering many promising technologies that have yet to fully unravel.

The aim of this research is to analyze and compare some of the most widespread crypto assets' valuation approaches within the framework of Big Data with a view to addressing their applicability and limitations. For the purpose of deriving meaningful insights, this investigation will first attempt to fully comprehend the diverse nature of crypto assets as well as their source of value. The next step will be to explore and apply some of the most widespread valuation approaches, using Bitcoin as the case study, with a view to assessing their applicability. Having evaluated and compared the different valuation methodologies, a vector autoregression (VAR) model will be developed to estimate the value of Bitcoin. The last step will consist in assessing the accuracy of the proposed model and outlining potential next steps.

In order to proceed with both, the assessment of crypto assets' valuation methods and the development of the VAR model, an analysis of both qualitative and quantitative nature will be carried out. On the one hand, the analysis could be classified as qualitative due to its focus on exploring some of the most widespread crypto assets' valuation methodologies. On the other hand, its nature is also quantitative given the fact that the research also deals with statistics and machine learning algorithms.

The dual nature of this methodology ensures the thorough understanding of crypto assets as well as their source of value, which will then serve as an input for developing the VAR model. Despite the thoroughness of the proposed methodology, there are some limitations inherent in it. First, the value drivers of crypto assets are often disagreed upon, thus complicating the identification and application of appropriate valuation approaches. Second, even though there are large amounts of easily accessible data regarding the market of crypto assets, it can be challenging to find accurate sources.

With a view to tackling this constraint and ensuring the quality and consistency of data, Big Data tools will be used to access traded data from reliable databases, with Messari being the main source of data. In this context, Big Data also becomes imperative to providing the necessary tools and data required to build the VAR model.

Even though the complexity inherent in the present research is rather high, finding appropriate valuation methods is critical for the crypto asset market. As of 26th May 2023, BTC was trading at $26,617.5 and the circulating supply was approximately 19.38 million BTC, indicating a circulating market capitalization of $513 billion[1]. Considering that BTC is only one of the 22,932 crypto assets in the market (Hicks, 2023), it is far from surprising that crypto assets are an investment opportunity to be taken into account when building a portfolio. Indeed, global crypto owners reached 425 million by the end of 2022 (Crypto.com, 2023). Even though crypto assets present potential investment opportunities, how to appropriately value these assets remains one of the most complex challenges of the market (Hougan and Lawant, 2021). The reasoning behind this lack of consensus regarding valuation approaches lies in how crypto assets differ from traditional assets in nature and thus in their value drivers. As a result, traditional valuation methods fail at appropriately reflecting crypto assets' value. Within this context, this research is the crucial catalyst to providing the inquisitive reader with some guidelines concerning their valuation and a potential valuation model to estimate the value of BTC.

This paper is structured in five main sections. The research begins with a theoretical framework that first explores the history, nature and taxonomy of crypto assets with the intention of providing an overview of the crypto asset market. This theoretical framework then introduces the lack of consensus regarding the valuation of crypto assets while listing some of the most widespread approaches, even though not recognized academically. Next, the methodology applied in the research is explained in detail, shedding light on the valuation approaches to be explored and the techniques employed in the development of the predictive model. Furthermore, the data needed to implement this methodology is listed in the next section. All of the above leads to the central focus of the research, the analysis. First, a correlation analysis is carried out to attempt to comprehend some of the factors that drive the value of BTC. The next step involves applying the selected valuation

[1] Data accessed using Python.

approaches to calculate the current value of BTC. Having done so, a predictive model will be built using the variables reviewed in the previous sections (if applicable) with a view to estimating the value of BTC. The final step of the analysis will consist of evaluating the accuracy and reliability of the predictive model with a view to providing an outline of next steps to be considered for the purpose of refining the proposed valuation model. Finally, conclusions will be drawn regarding the lack of consensus regarding valuation approaches.

2. THEORETICAL FRAMEWORK

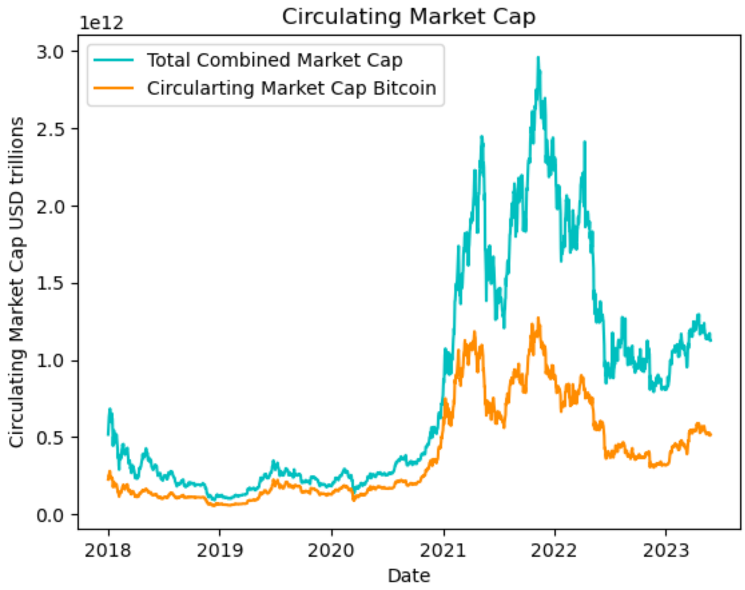
2.1 Conceptual framework

2.1.1 Bitcoin as the pacesetter for crypto assets

Crypto assets were first introduced to the world in the form of Bitcoin back in 2009. Following the 2008 financial crisis, a pseudonymous author published the white paper *Bitcoin: A Peer-to-Peer Electronic Cash System* (Nakamoto, 2008). Essentially, this paper was a proposal to implement a peer-to-peer network applying blockchain technology with a view to addressing the limitations of the centralized banking system, which became apparent following the collapse of Lehman Brothers. According to Nakamoto (2008), BTC would foster a system for electronic transactions that would allow individuals to hold and transact items of value without relying on trusted intermediaries. Shortly afterwards, on 3rd January 2009 “the software was released, the first bitcoin was minted, and the BTC network was launched” (Hougan and Lawant, 2021, p.2).

Nobody could have ever predicted back then that, almost 15 years on, BTC would hit a $513 billion market capitalization as of 26th May 2023. Not only has it grown exponentially but it has also given rise to the ascent of crypto assets. In fact, according to Panetta (2022) crypto assets boast a combined market capitalization of approximately $1.1 trillion. Since then, this figure has further increased.

Figure 1: Market capitalization (BTC and combined).



Source: own elaboration.

As aforementioned, BTC was the first crypto asset to ever exist and still remains the most prominent as of today, representing 45% of the combined crypto asset capitalization. Most importantly, BTC opened the way for other blockchain and crypto projects to emerge (Hougan and Lawant, 2021). Following this line of thought, understanding how BTC works and what its value drivers are is the crucial catalyst to providing a solid foundation for the valuation of crypto assets.

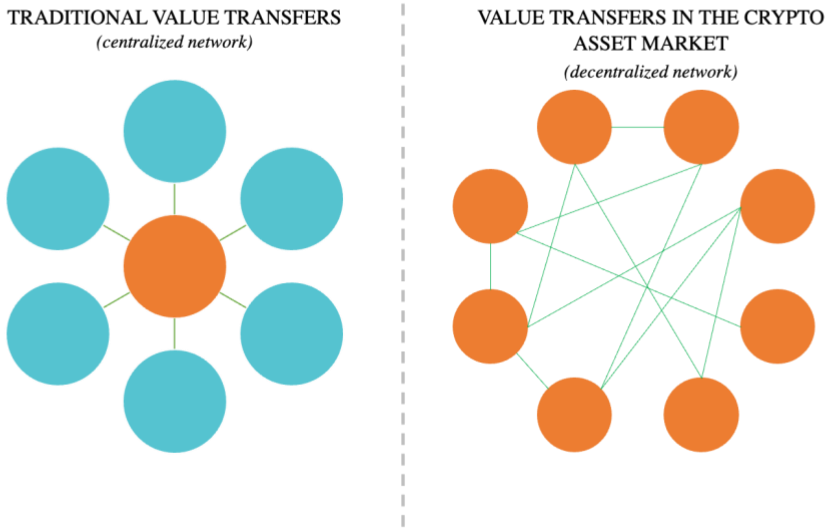
2.1.2 Understanding the nature of crypto assets

Despite the obvious economic relevance of crypto assets, they are still greatly misunderstood by individuals, thus complicating their valuation further. With a view to providing a thorough understanding of their nature, this section will attempt to give a brief overview of BTC and its core technical architecture.

As aforementioned, BTC could be defined as a distributed ledger accessible to everyone that does not necessarily rely on trust intermediaries but rather employs peer-to-peer software and cryptography to record transactions of items of value (Lamothe Fernández and Lamothe López, 2020).

How this decentralized database is structured in order to allow transactions of value directly on a peer-to-peer basis is shown in Figure 2.

Figure 2: Value transfers in traditional and crypto asset markets.

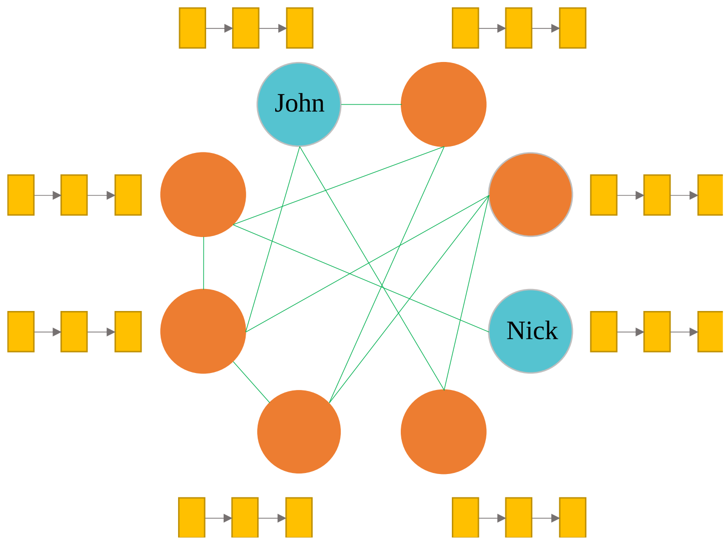


Source: adapted from Hougan and Lawant (2021).

Benefits of a database with these features are evident. As stated in Hougan and Lawant (2021, p.3), “if every party can agree on the status of the database at any time, the delays required to allow Database A to sync with Database B can be massively reduced”. Nevertheless, this fairly simple concept poses several challenges such as the reliability and accuracy of the consensus. How the formation of such consensus works is better understood through an example. However, before diving in it is worth noting that BTC payments are available to anyone with the ‘requisite software’, otherwise known as a wallet. Each wallet has two encryption keys, one is public to the ‘BTC network’ and acts as an address or account number while the other key is private.

If John, for example, wanted to send 3 bitcoins to Nick, he would need to write a payment order using the latter’s public key. This message would then be sent to all nodes of the BTC network that keep the ledger updated. However, in order for these nodes to make sure it comes from John; he uses his private key to encrypt the message, which can only be de-encrypted using his public key. Following this line of thought, someone de-encrypting the message could confirm it was John who sent it (Segendorf, 2014). Nevertheless, at this point the transaction has just been proposed. This process is represented in Figure 3, with John and Nick being represented as blue circles and the updated copies of the database as orange rectangles.

Figure 3. Transaction request.



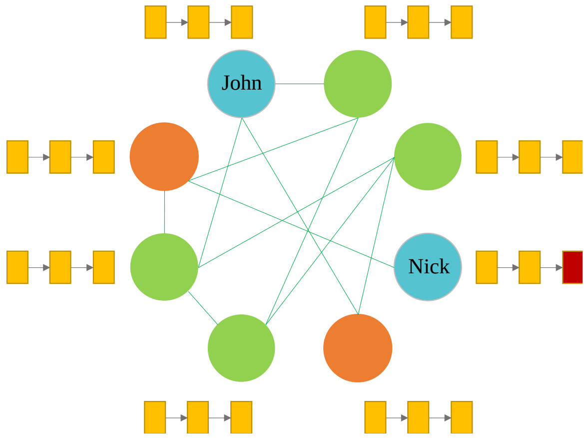
Source: adapted from Hougan and Lawant (2021).

Following John's request to send 3 bitcoins to Nick, the transaction needs to be verified, which is when miners (represented in Figure 4 as green circles) come into play. Every ten minutes approximately the proposed transactions that have been broadcasted to the BTC network (including John's) are aggregated by miners into blocks in a quest for adding them permanently to the blockchain. In short, the blockchain is where verified transactions are registered. In order for these payments to be verified, miners need to solve a very complex mathematical problem. The incentive to solving this mathematical puzzle consists of "newly minted bitcoin and potentially transaction fees paid by the sender of the payment" (Hougan and Lawant, 2021, p.5). Considering that bitcoins are rewarded to miners, it is not surprising that the growth of BTC USD derived in a very competitive mining industry (Kubal and Kristoufek, 2022).

With a view to understanding the process of verification one must comprehend the concept of hash rate. While the hash is an attempt to solve the aforementioned mathematical problem, hash rate refers to the "combined computing power dedicated to mining" and depends on both the mining efficiency and the amount of electricity employed by the network (Kubal and Kristoufek, 2022, p.1).

Returning to the example, once a miner solves the cryptographic problem it proposes the block of transactions to the network. Nevertheless, at this point only the successful miner can see the fully updated ledger with the newly proposed block (represented as a red rectangle in Figure 4) and John's transaction is not settled yet.

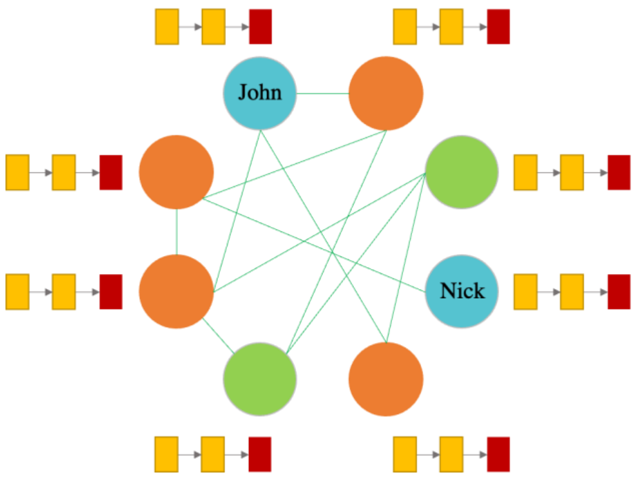
Figure 4. Solving the mathematical problem.



Source: adapted from Hougan and Lawant (2021).

The next step consists in other miners checking whether these transactions are valid, which is a fairly easy task. If so, the rest of participants of the BTC network will update their ledgers to reflect the new transactions (Figure 5).

Figure 5. Updating ledgers.



Source: adapted from Hougan and Lawant (2021).

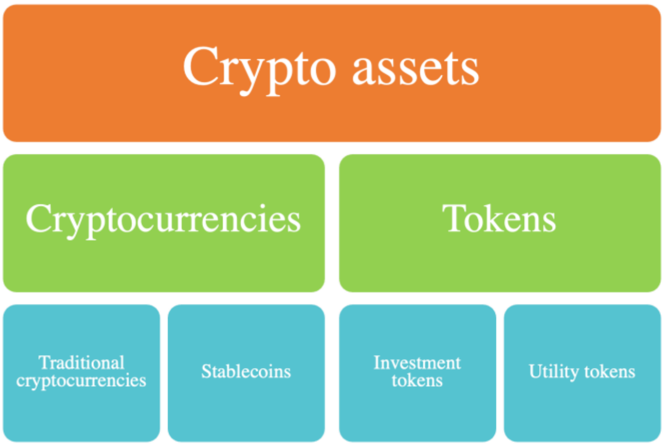
Having understood how BTC transactions work, it is worth mentioning that the supply of bitcoins is limited to 21.000 million units (Boar, 2018), something to be considered later on.

2.1.3 Categorizing crypto assets

Even though BTC's technical core structure does not reflect the technology behind all crypto assets, it does certainly provide a general understanding of what they are. While there is no generally agreed upon lexicon, crypto assets could be defined as "digital representations of value used for a variety of purposes such as payments, investments or access to goods and services, that rely on distribute ledger or similar technology" (Feyen et al., 2022, p.2).

In summary, the term 'crypto assets' refers to a broad array of assets, though their taxonomy is not yet established formally. The main reason behind this is the continuous evolution of the crypto asset market. Since new types of assets are emerging, their taxonomy will most likely keep changing (Houben and Snyers, 2020). For the sake of the simplicity of the research only broader categories of crypto assets (represented in Figure 6) will be identified and explained.

Figure 6. Taxonomy of crypto assets.



Source: adapted from Houben and Snyers (2020).

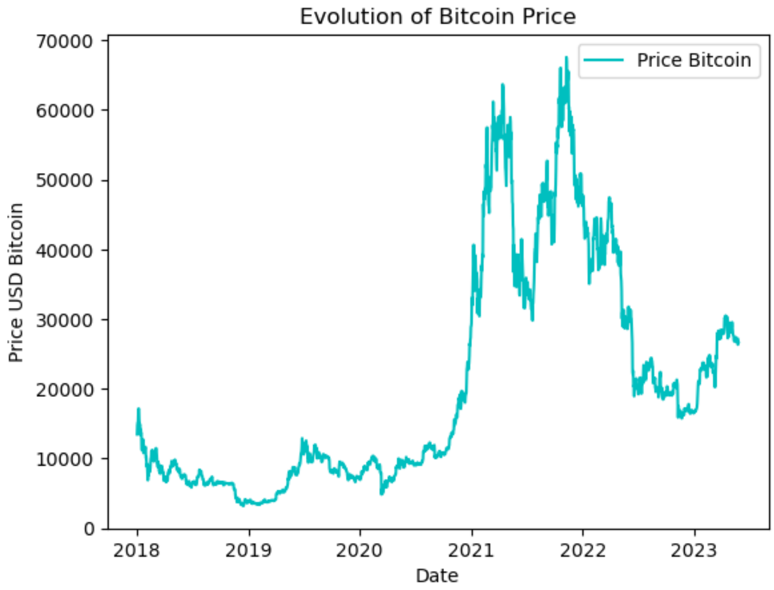
More broadly, a *summa divisio* can be made between cryptocurrencies and tokens. On the one hand, cryptocurrencies could be defined as digital currencies for which "ownership and transfers of ownership are guaranteed by a cryptographic decentralized technology" (Giudici et al., 2020, p.1). Their purpose as digital currencies are to function as a medium of exchange, store of value and a unit of account. The first wave of cryptocurrencies started with BTC and could be referred to as traditional "non-backed" cryptocurrencies (Houben and Snyers, 2020). In other words, they have no underlying asset, liability, or claim (Manaa et al., 2019). This lack of underlying value derives in high volatility, a common feature amongst non-backed cryptocurrencies, which poses an obstacle to carrying out their role as currencies. With a view to tackling their severe price volatility, stable coins emerged (Bullman et al., 2019). While stable coins are similar to traditional cryptocurrencies in the sense that their purpose is also to perform as digital currencies, they differ from the latter because they typically represent an underlying claim or asset. In other words, since they are linked to other fiat currencies and bank deposits, amongst other assets, they maintain a stable value (Melo et al., 2022).

On the other hand, tokens are digital assets that, unlike cryptocurrencies, don't have their own blockchain or distributed ledger but are rather built on top of an existing one (Di Angelo and Salzer, 2020). Moreover, they offer their owners economic, governance, utility, or consumption rights (Houben and Snyers, 2020). Depending on the rights they grant, they are commonly classified as 'investment'/'security' tokens or 'utility' tokens. The former category of tokens consists of those assets that represent a debt or equity claim on the issuer and are thus similar to equities, bonds, or derivatives (Di Angelo and Salzer, 2020). On the other side of the spectrum, utility tokens give their holders access to a product or service (Kaal, 2022).

2.1.4 Crypto assets differ greatly from traditional assets

From the above, it is evident how crypto assets differ immensely from traditional assets such as equity or bonds. Since their launch, many crypto assets, and more specifically BTC, have been characterized primarily by high returns and high volatility (Hougan and Lawant, 2021).

Figure 7. BTC USD.

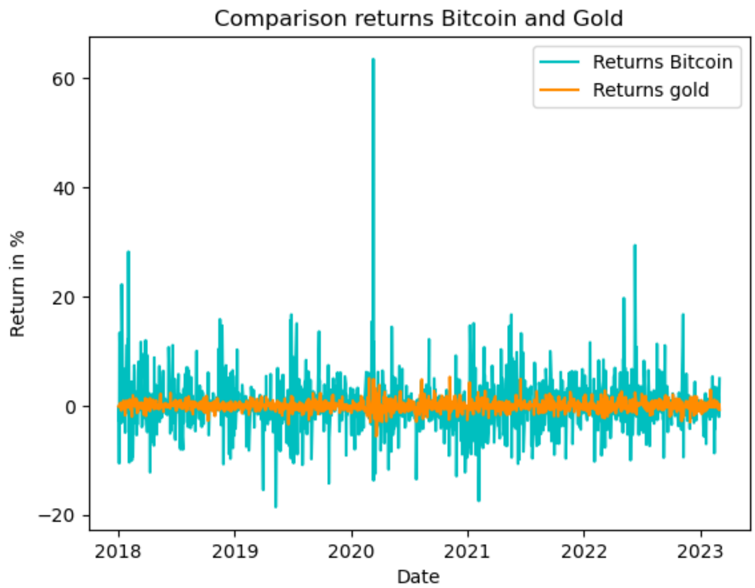


Source: own elaboration.

Their significantly high returns to other assets are evident in longer term graphs. As data in Figure 7 shows, BTC USD rose from approximately $9500 (as of 8th March 2020) to almost $60000 one year after. In other words, the rate of return was as high as 530%, thus making it an investment opportunity to be taken into account.

Nevertheless, such returns come along with an even higher volatility and the same way BTC USD suddenly rises, it also drops significantly. For instance, as of 21st April 2021 BTC USD surpassed $56000 but just two months later it plunged to almost $35000. Moreover, this volatility is not only present on an annual or monthly basis, but also on a daily and even intraday basis (Kim et al., 2021). The unpredictability of the crypto assets seems even higher when compared to traditional assets. Figure 8 compares the returns of both BTC and gold reflecting the obvious differences in volatility levels (Klein et al., 2018).

Figure 8. Returns BTC and gold.



Source: own elaboration.

2.1.5 Value of crypto assets

Having seen how crypto assets differ from traditional assets in terms of both structure and purpose, it is not surprising that their value drivers also diverge. For instance, the price of equities is primarily driven by corporate operating/financial performance and growth opportunities (Giudici et al., 2020). Bonds, however, are mainly driven by interest rates and inflation. Since crypto assets are neither shares of ownership in a company nor debt securities, their value drivers are not the same. Subsequently, traditional valuation approaches don't necessarily apply to crypto assets and therefore other methods should be explored.

In broader terms, according to Burniske and Tatar (2017) there are two types of value that the community of crypto asset users place on these assets: utility value and speculative value. On the one hand, since crypto assets are still an early-stage investment opportunity (Hougan and Lawant, 2021) speculative value comes into play. This means that some of crypto assets' value is driven by how widely used people think they will become in the future. While speculative value is extremely complex to assess, the development team of a crypto asset is an element to take into consideration since people will generally have more faith on a crypto asset if it was created by a renowned and skilled team.

On the other hand, utility value refers to the usefulness of the crypto asset. In other words, it reflects what users gain through crypto assets from accessing their digital resources. In the case of BTC, users benefit from quick and efficient transfer of value to basically anyone. For Ethereum on the other hand, users can deploy decentralized applications or smart contracts without the risk of fraud and avoiding third party intermediaries.

Taking into account that, as a crypto asset matures, people will begin to understand what the market penetration will be like for that specific crypto asset, it is not surprising that those assets with higher maturity will converge on its utility value (Burniske and Tatar, 2017).

2.1.6 Utility value as the key to valuing crypto assets

As aforementioned, estimating speculative value in new crypto assets depends on predicting their expected rate of adoption and having a good basis of their future value. Consequently, investors might find this a quite complicated task. The complexity of estimating the value of new crypto assets also derives from not fully grasping how unique and valuable the implementation of their blockchains is. More mature crypto assets, however, have been around long enough and are thus easier to understand. As a result, and for the sake of simplicity, this section will focus on analyzing what variables drive utility value.

According to Burniske and Tatar (2017), whose views have been supported by other investors such as Bheemaiah and Collomb (2018), utility value is mainly driven by supply and demand characteristics. Concerning the former, understanding the current rate of supply as well as the total planned supply of an asset is imperative in this context. In more detail, if a crypto asset has a high rate of supply issuance but its utility value is not growing in line with the increase in supply, its value will be diminished. The same thing happens with total planned supply. In the case of BTC, Satoshi decided to cut in half the amount of bitcoin issued every 210,000 blocks mined because if 1.9 million bitcoins kept being issued on a yearly basis, as it happened during the first year of BTC (Best, 2022), it would eventually erode its value. This is the reasoning behind BTC having the aforementioned supply of 21 million bitcoins.

Following the concept of scarcity driving value, demand comes into play. As more people want to use a crypto asset, the more they will have to pay to access it. Demand can be potentially represented as number of users, number of transactions and the dollar value of transactions, otherwise known as volume.

Regarding the number of users, a metric that better depicts this concept is active users (Jernej & Kovačič Batista, 2018), which represents the number of wallet users that are active in the network (Burniske and Tatar, 2017). In this context, another metric to be considered is active addresses, which represents the number of originators or recipients of transactions in the network. Another meaningful metric is the number of transactions, since it reflects the frequency of use and can thus be a useful indicator of demand. Following this line of thought, one must also take into account the monetary value of transactions.

As mentioned above, these transactions must be verified my miners, who need to solve a very complex mathematical function which entails finding the solution to a 'hash' function (Söderberg, 2018). In order to do this, miners need to employ significant computational power to randomly create proposed solutions to the hash function. In exchange for their work, in the case of BTC, miners can either receive newly minted bitcoin, which is the process by which bitcoins are created, or receive transactions fees paid by users when making payments in the network. This process is highly linked to the rate of supply since every 210,000 blocks mined the rate of bitcoins released into circulation are cut in half and so are miners' rewards in native units (Meynkhard, 2019). Transaction fees, however, depend on demand characteristics. In other words, there is a limit regarding how many transactions fit into a block and thus, when too many users are proposing transactions, extra rewards can be paid voluntarily to speed up their validation. In summary, metrics such as miners' revenues or hash rate are also highly linked to supply and demand characteristics.

2.2 Literature review

Understanding the two types of value associated to crypto assets is relatively straightforward. However, identifying and comprehending the factors that drive their value is a highly complex task and more so considering how they differ from traditional assets in their structure, technology, and value drivers. In other words, the main uncertainty surrounding crypto assets does not lie on whether they carry value but rather on how to properly value them. In fact, their valuation has been a “hotly debated topic within both industry and academia” (Carter, 2019, p.69). This lack of consensus has derived in the development of a vast array of valuation approaches (primarily concerning BTC) which has further complicated reaching an agreement on this matter. Consequently, this section will focus on providing the inquisitive reader with an overview regarding the most widespread valuation approaches in the context of crypto assets.

Despite the lack of consensus regarding valuation methods, Hougan and Lawant (2021) believe that the total addressable market model is the most widespread valuation approach. Authors who also explore this valuation method in detail include Chan and Hasan (2020).

According to Chan and Hasan (2020), TAM is a market size variable that represents the overall revenue opportunity that is available to a product or service if the full market share was achieved. In the context of crypto assets, we could consider crypto currencies and tokens as products. Having understood what TAM is, we can now comprehend the purpose of this model, which is to estimate crypto assets’ addressable markets and compare them to their current market capitalization.

One of the main advantages of this model is that it can be easily escalated due to its simplicity. However, authors such as Hougan and Lawant (2021) argue that simplicity is also one of its limitations. The main issue lies in the fact that the input variables for the TAM model are all assumptions, which makes it extremely complex to obtain an accurate estimate of the total addressable market.

Another traditional valuation approach that has been adapted to the crypto asset market is the quantity theory of money. This theory was originally introduced by theologist Martín de Azpilicueta in 1556 (Dimand, 2018) and later developed by Fisher (2011). The ‘Fisherian theory’ basically states that changes in price can derive from changes in the money supply, implying that both variables have the same growth rates in the long term (Dimand, 1997). In more detail, it states that the value of a currency depends on both, the size of the market it supports and the velocity at which it moves through it (Hougan and Lawant, 2021). The formula is as follows:

$$M * V = P * Q$$

Although the taxonomy of crypto assets is very diverse, they originally served as a store of value and means of exchange when BTC emerged. Hence, crypto assets could be regarded as currencies in the market they support (Burniske, 2017), which explains why the equation of exchange comes into play.

One of the most popularized approaches in the context of crypto assets regarding the quantity theory of money is the valuation model proposed by Chris Burniske in both, the book Cryptoassets: *The Innovative Investor's Guide to Bitcoin and Beyond* (Burniske and Tatar, 2017) and the article *Cryptoasset valuations* (Burniske, 2017).

Despite being one of the most widespread frameworks for the valuation of crypto assets, some authors have questioned its ability to properly reflect their value. For instance, according to Hougan and Lawant (2021) one of the main challenges of this valuation model is estimating velocity, which is quite a complex task due to crypto assets' high volatility.

Another valuation approach that has been adapted according to the nature and features of crypto assets is the Network Value to Transactions ratio, which is based on the price-to-earnings ratio (P/E), a highly relevant ratio used in the valuation of stocks. This ratio, which was first introduced by Woo (2017), is quite interesting since it was the first approach that looked into network variables in an attempt to tailor existing methods to crypto assets' characteristics. The formula for the P/E ratio is as follows:

$$P/E = \frac{Share\ price}{Earnings\ per\ Share}$$

Since crypto assets don't represent companies and therefore don't generate earnings, the P/E ratio could not be applied to value crypto assets. However, Woo (2017) argued that BTC could be considered as a payments and store of value network. Thus, the money flowing through it (transaction volume) could be considered as a substitute to company earnings. Essentially, this ratio compares a crypto asset's market capitalization to the daily on-chain transaction volume, which potentially reflects the utility users derive from the network (Bheemaiah and Collomb, 2018). The formula is as follows:

$$NVT = \frac{Network\ Value}{Daily\ transaction\ volume}$$

In essence, the NVT ratio may indicate whether the price of the crypto asset in question has surpassed or fallen below the value implied by its underlying daily transaction volume in USD. For instance, if BTC's NVT ratio is high compared to its competitors it could be argued that it is overvalued.

Benefits of this valuation approach include simplicity and its potential to detect bubbles which is especially relevant in the crypto asset market given its significant volatility. Nevertheless, this does not necessarily mean that NVT can predict bubbles but rather that it enables investors to discern between consolidation of price and bubbles (Woo, 2017). In more detail, if following a price explosion, the NVT ratio remains within its average range we would be looking at a consolidation of price rather than at a bubble. However, an increase of the NVT ratio above average would indicate a bubble. In this case, transactional activity could not be able to sustain such a high valuation and thus a lengthy price correction would be expected.

Despite this valuation method being a step in the right direction, there are some limitations to it. According to Yang and Fantazzini (2022) the NVT ratio is very volatile and thus is a quite difficult indicator to apply. Due to NVT's limitations, Kalichkin (2018) attempted to smooth the denominator with the 90-day moving average to get rid of the time lag issue.

$$NVTS = \frac{Network\ Value}{MA_{Transaction\ Volume}}$$

Other adaptations of the NVT ratio include the Network-Value-Realized-Value ratio, which was developed by Puell (2018).

$$NVRV = \frac{Network\ Value}{Realized\ value}$$

The purpose of this approach was to adjust the NVT ratio for two elements of BTC, lost coins and coins used for "hodling". On the one hand, lost coins are bitcoins whose private keys are lost and thus can no longer be spent. According to Popper (2021), of the 18.5 million bitcoins that were in circulating at the time the article was written, 20% of them appeared to be lost. The percentage of bitcoins lost amounted to almost $140 billion. On the other hand, "hodling", otherwise known as "hold on to dear life", refers to the strategy of not selling crypto assets in spite of price changes in the market (Yogarajah, 2022).

Another adaptation that does not only include network metrics but also cost metrics is the Network-Value-Hashrate ratio, which was explored by Yang and Fantazzini (2022).

$$NVHR = \frac{Network\ Value}{Hash\ rate}$$

This ratio measures the value in dollars of a crypto asset's network per unit of hash rate. Regarding its interpretation, Yang and Fantazzini (2022) explain two different approaches. On the one hand, a high NVHR might indicate the willingness of investors to further invest in the market because of positive expectations. On the other hand, it might signify that investors are willing to pay more not only because they have positive expectations of the market but also because of the economic security granted by the hash rate. The latter concept is particularly relevant in the context of crypto assets since their degree of utility depends on the security granted by their underlying blockchains.

The above leads us to the conclusion that there are several approaches deriving from the NVT, though none of them are academically recognized.

While the NVT was the first valuation approach to consider network attributes rather than the typical financial models (Bheemaiah and Collomb, 2018), it failed to take into account a highly relevant value driver, active addresses.

As mentioned above, the term "active addresses" refers to the number of unique individual accounts that are active on a network. According to Fantazzini and Yang (2022), valuation models that include active addresses in their calculations are either derived from Metcalfe's law or Odlyzko's law.

The valuation approach derived from Metcalfe's law is the most widespread amongst the two theories and is based on the work carried out by Robert Metcalfe regarding Ethernet in the 1980s. For further details regarding the original theory refer to “40 years of Ethernet” in *Computer* (Metcalfe, 2013).

As specified by Fantazzini and Yang (2022), Metcalfe’s law was developed with the purpose of modelling the network effect of communication technologies such as fax machines or telephones. Metcalfe's law states that the value of a network is proportional to the square of the number of participants. In synthesis, this rationale is formulated as follows:

$$ML_{Value} = A * \frac{n * (n - 1)}{2}$$

The terms of the equation include A (a coefficient) and n (number of active users on the network). Examples of authors that have opted for Metcalfe’s law when valuing crypto assets include Van Vliet (2017), Wheatley et al. (2018) and Alabi (2017). The work of Alabi (2017) is perhaps the most widespread within the crypto asset community and is based on the re-formulation of Metcalfe’s value by Gilder (1993) in “Metcalfe’s Law and Legacy”.

$$ML_{Value} = A * n^2$$

It is worth mentioning that the relationship between the value of a network and the number of active users in the latter formula is not linear but rather square. For instance, the value of a network with 5 users is 25 (5^2) (Hougan and Lawant, 2021).

Alabi (2017) popularized this valuation approach in “Digital Blockchain Networks Appear to be Following Metcalfe’s Law”, where it was concluded that the value of a network is proportional to the square of its users. As a result, Metcalfe’s law in the crypto asset market can be formulated as follows:

$$ML_{Value} = n^2$$

This valuation approach has been widely accepted within the crypto asset community not only because it is fairly easy to understand and carry out but also because it makes intuitive sense. Nevertheless, as with any valuation approach in the context of crypto assets, there are a few limitations to it.

One of the main drawbacks regarding Metcalfe’s law is that it places equal weight on all active users. This is not entirely accurate since users that hold a significant amount of crypto assets must be differentiated from others at some extent. Hougan and Lawant (2021) provide the example of Paul Tudor Jones II allocating 2% of his portfolio in BTC and compare it to a new client (Lucy) buying her first $100 of bitcoin. Evidently, the former’s impact on BTC is significantly higher to that of Lucy’s.

The latter limitation has not gone unnoticed. As a result, crypto researchers such as Briscoe et al. (2006) have built upon the latter approach to reflect the incremental value of adding another user to a network of n users. According to the mathematician Andrew Odlyzko, who re-formulated Metcalfe’s law in “Metcalfe’s law is wrong - communications networks increase in value as they add members-but by how much?” (Briscoe et al, 2006), the value of a network can be approximated as:

$$OL_{Value} = n * \log(n)$$

Another approach that attempted to adapt an already existing valuation approach to crypto assets is the stock-to-flow model. This approach was popularized in the context of crypto assets by the pseudonymous author PlanB (2019) and is based on the concept of scarcity. The latter is extremely relevant when referring to BTC since “Bitcoin is the first scarce digital asset the world has ever seen” (PlanB, 2019). Recapitulating, BTC is considered to be scarce because Satoshi Nakamoto decided to set a total planned supply of 21 million bitcoins to maintain their value in the long-term. Something similar happens to gold, a commodity that has managed to maintain its monetary supply throughout history due its low rate of supply (Ammous, 2018).

In theory, the scarcer a resource is, the better store of value it is. In other words, if a resource is relatively scarce, it should retain its value over prolonged periods of time. The stock-to-flow ratio measures the concept of scarcity and is calculated as follows:

$$Stock - to - flow = \frac{Stock}{Flow} = \frac{Circulating\ supply}{Annual\ flow\ of\ production}$$

Table 1 is particularly relevant with a view to fully understanding the reasoning behind this valuation approach:

Table 1: Stock-to-flow commodities (PlanB, 2022).

	Stock (tn)	Flow	SF	Supply growth	Price $/Oz	Market value
Gold	185,000	3,000	62	1.6%	$1.300,00	8,416,500,000,000
Silver	550,000	25,000	22	4.5%	$16,00	308,000,000,000
Palladium	244	215	1.1	88.1%	$1.400,00	11,956,000,000
Platinum	86	229	0.4	266.7%	$800,00	2,400,000,000

Source: own elaboration.

As stated by Ammous (2018), gold has the highest stock-to-flow ratio of commodities. Essentially, having an SF of 62 means that it would take 62 years of production to achieve the current stock of gold. Except for silver, the rest of commodities have an SF that is barely higher than 1. Taking a closer look at Table 1, the market value tends to be higher when the SF is also high, confirming the underlying hypothesis of the model of scarcity driving value.

In the case of BTC, its scarcity is calculated as follows:

$$Stock - to - flow = \frac{Stock}{Flow} = \frac{Circulating\ supply\ Bitcoin}{Annual\ flow\ of\ production\ bitcoins}$$

This ratio expresses the relationship between the value of BTC and the amount of new bitcoin minted on a yearly basis, thus reflecting the idea of BTC USD being driven by scarcity.

Again, this valuation approach is highly relevant in the context of BTC since it reflects what many investors believe to be one of its dominating features, scarcity (Hougan and Lawant, 2021). Nevertheless, being tailored to BTC at such extent is also perceived as one of limitations of the model. In other words, because the main and only focus of the stock-to-flow ratio is the concept of scarcity, its application is not fitting when valuing other crypto assets that have unlimited supply, such as Ethereum (Angela and Sun, 2022).

Another valuation approach worth mentioning explores the relationship between mining costs and the value of crypto assets. The cost of production model is a valuation approach introduced by Hayes (2015) in “A cost of production model for Bitcoin”. As stated by

Hougan and Lawant (2021), the rationale behind the cost of production model is that crypto assets can be considered commodities and, as a result, are subject to "traditional pricing challenges on the supply side" (p.19). This reasoning led Hayes (2015) to suggest that the cost of producing each marginal bitcoin should align with its price. Since miners are paid in the form of either newly minted bitcoins or transaction fees, miners will keep producing bitcoin until their marginal costs equal their marginal revenue. Consequently, the value of BTC can be estimated by comparing the marginal cost of producing bitcoins to the expected yield of miners.

Despite empirical studies carried out by Adam Hayes show significantly high correlation between BTC USD and marginal cost (Hougan and Lawant, 2021), there are a few limitations regarding this model. First, even though it includes electricity costs in its calculations, it fails to account for capital and operating expenditure (CapEx and OpEx). This implies that costs that costs inputs such as purchases, regulatory, labor, and pooling fees are ignored and thus, costs can be undervalued.

Another limitation includes that some inputs cannot be directly determined but must rather be assumed, such as the cost of electricity, with some miners even having free (Stoll et al., 2019).

Most importantly, some authors such as Fantazzini and Kolodin (2020) question the causality of the relationship between BTC USD and marginal cost. In other words, the mining rate depends on the total planned fixed supply rather than on price, which might suggest that BTC USD drives the cost of production, not vice versa. The causality between BTC USD and margin cost is not the only relationship being questioned, with some authors such as Kjærland et al. (2018) arguing that the hashrate does not impact BTC USD.

3. METHODOLOGY

As it can be observed, there is no consensus regarding the applicability of crypto asset valuation approaches. Consequently, further research is need in this context with a view to getting an overview of the state of current methods.

3.1 Main objectives

Recapitulating, the aim of this research is to provide an overview of commonly used methods in the crypto asset community so that the inquisitive reader can then assess their applicability and limitations when valuing crypto assets. Considering that this research focuses on reviewing different valuation approaches, it will provide a solid foundation for understanding the underlying factors that drive the value of Bitcoin. Consequently, the next logical step is to build a VAR model to attempt to estimate the value of Bitcoin.

3.2 Scope of the research

Having observed the variety of crypto assets in the market, analyzing valuation approaches that would fit them all would be very time-consuming. For the sake of simplicity of the report, we will focus on the valuation of BTC since it was the first crypto asset to ever exist and still is the most dominant asset of the market. Furthermore, returning to the concept of utility value, BTC is the most mature of them all and is thus further along the transition from speculative value to utility value.

3.3 Methodology breakdown

3.3.1 Analyzing the value drivers of crypto assets

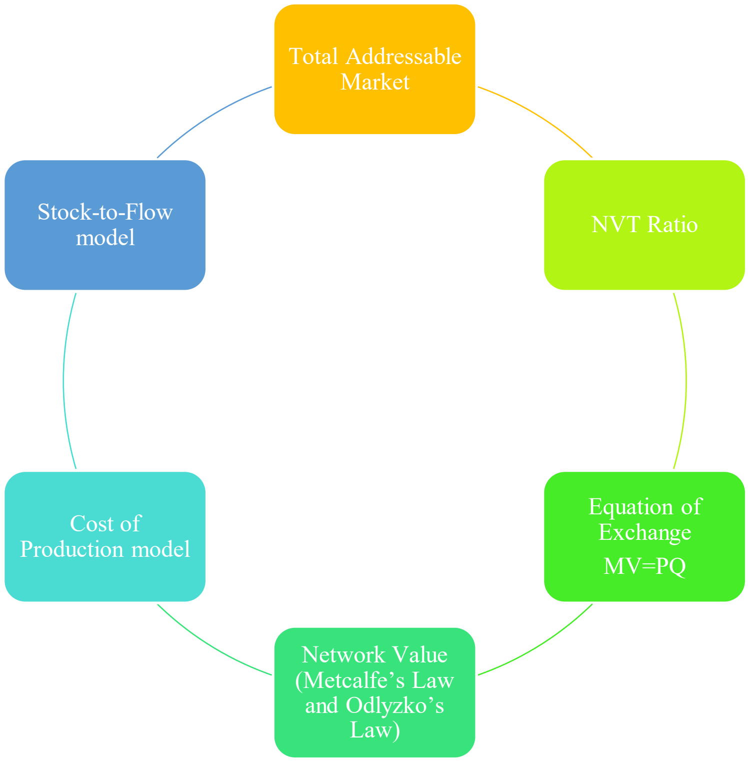
Having explored the fundamentals of crypto assets in the theoretical framework, the first sub-question of the analysis lies in identifying the value drivers of crypto assets, and more specifically BTC. For this purpose, empirical evidence will be presented to show how the selected value drivers may lead BTC USD. Variables for whose correlation with BTC USD is explored include:

- BTC volume
- Circulating Supply
- Hashrate
- Active Addresses
- Daily Blocks Mined
- Number Transactions
- Fees in native units (no issuance)
- Sum of all miner revenue

3.3.2 Valuing Bitcoin through different approaches

Since there are no academically recognized valuation approaches (Jernej and Kovačič Batista, 2018), the next sub-question will focus on looking into the existing methods that are most commonly applied in the community. This step will involve estimating the worth of BTC using valuation approaches that have received greater support from the academic literature and that align with the value drivers identified in the previous section. Figure 9 summarizes the valuation methods to be explored.

Figure 9: Valuation approaches to be explored.



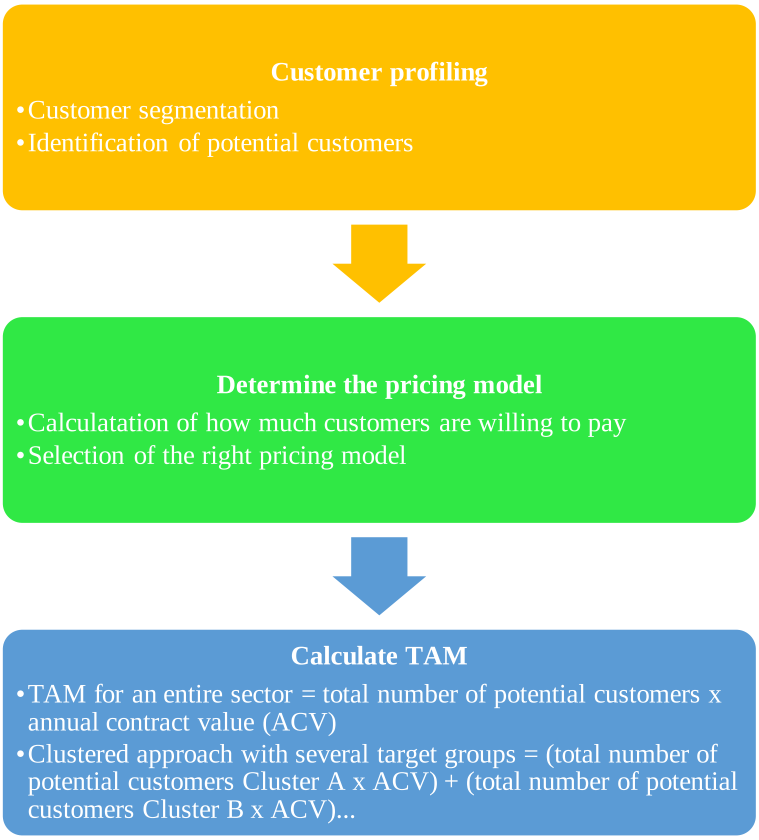
Source: own elaboration.

3.3.2.1 Total Addressable Market

Since estimating TAM is highly complex, Chan and Hasan (2020) developed a simplified methodology (Figure 10) to calculate addressable markets for blockchain solutions.

Taking into account that blockchain is the underlying technology of crypto assets, this methodology could also be applied to the latter with a few adjustments.

Figure 10: Methodology TAM Simplified (Chan and Hasan, 2020).



Source: own elaboration.

Since carrying out the above methodology would be very time consuming, a simplified example will be shown to illustrate how to value BTC using the TAM model. More in detail, BTC's TAM will be estimated using the USD value of the gold market as a proxy. As specified by Kyriazis (2020), literature regarding the nexus between gold and BTC is increasing in importance, with many people believing the former might be a potential non-sovereign store of value (Hougan and Lawant, 2020). Estimating the value of BTC using the TAM model involves the following steps:

- Calculate the USD value of the gold market.

$$USD\ value\ of\ total\ market\ gold = mined\ tonnes\ of\ gold * 32{,}000\frac{oz}{tonne} * price\frac{gold}{ounze}$$

- Make assumptions regarding the percentage of the gold market that BTC is projected to capture.
- Calculate BTC's implied value.

$$Implied\ value\ BTC = \frac{USD\ value\ of\ total\ market\ gold * \%\ of\ the\ market\ capture\ by\ BTC}{Total\ planned\ supply\ BTC}$$

3.3.2.2 NVT Ratio

With a view to providing the inquisitive investor with a thorough overview of crypto assets' valuation methods, this research will go beyond the NVT ratio by exploring a few of its adaptations. The ratios to be analyzed along with their respective formulas analyzed are listed below:

- NVT ratio.

$$NVT = \frac{Network\ Value}{Daily\ transaction\ volume}$$

- NVTS ratio.

$$NVTS = \frac{Network\ Value}{MA_{Transaction\ Volume}}$$

- NVRV ratio.

$$NVRV = \frac{Network\ Value}{Realized\ value}$$

$$Realized\ value = \sum_i Last\ trade\ price\ of\ each\ coin$$

- NVHR ratio.

$$NVHR = \frac{Network\ Value}{Hash\ rate}$$

- NVHRS ratio.

$$NVHRS = \frac{Network\ Value}{MA_{Hash\ rate}}$$

It is worth mentioning that the NVT ratio (or its adaptations) does not provide an estimation of BTC USD but rather serves as an indicator the determine whether BTC USD has surpassed or fallen below the value suggested by the transaction volume (or other metrics employed in the different adaptations).

3.3.2.3 Stock-to-flow

Applying this valuation approach will be relatively simple compared to the rest of selected methodologies as it only involves calculating the stock-to-flow ratio using the following formula:

$$Stock - to - flow = \frac{Stock}{Flow} = \frac{Circulating\ supply\ Bitcoin}{Annual\ flow\ of\ production\ bitcoins}$$

3.3.2.4 Quantity theory of money

With a view to calculating the value of BTC using the quantity theory of money, the variables in the equation of exchange must be understood. Definitions of M, V, P and Q are shown in Table 2:

Table 2: Terms Quantity Theory of Money (Hougan and Lawant (2021).

Term	Traditional meaning	Meaning in crypto asset market

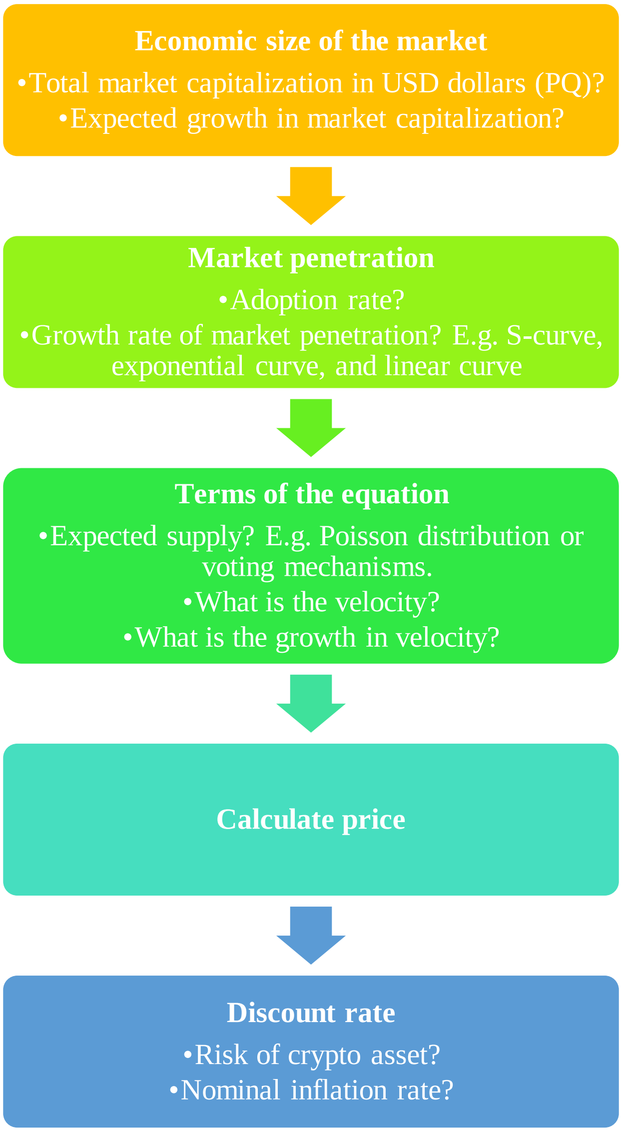
M	Total money supply	Crypto asset market capitalization
V	Velocity: average frequency with which a unit of money is spent	Velocity: average frequency with which a unit of the crypto asset is spent
P	Price of goods and services	On-chain transaction volume
Q	Quantity of goods and services	Number of transactions executed in the period analyzed

Source: own elaboration.

Although the meaning of the terms of the equation of exchange varies significantly when adapted to crypto assets, the underlying rational is the same: the value of the transactions that are executed within a market must equal the existing money supply times the average frequency at which it is exchanged or spent.

As aforementioned, Burniske (2017) adapted the quantity theory of money to develop a valuation approach for crypto assets:

Figure 11: Methodology Equation of Exchange.



Source: own elaboration.

Considering the complexity and the challenges implied in estimating BTC USD using the above approach, a simplified methodology will be applied. The steps to be followed are listed below:

- Calculate velocity.

  $V = (P * Q)/M$

- Calculate circulating supply.

$$\begin{aligned} Circulating\ supply_{End\ 2023} \\ &= Current\ Circulating\ Supply \\ &+ Monthly\ Average\ Rate\ of\ Bitcoin\ Issued \\ &* Remaining\ Months\ of\ 2023 \end{aligned}$$

- Calculate the implied price of BTC.

$$P_u = \frac{P * Q}{V * Circulating\ supply}$$

3.3.2.5 Active addresses

Since the Metcalfe's Law attempts to estimate the value of a network, it could be used in conjunction with the NVT ratio with a view to assessing whether BTC USD has fallen or surpassed its underlying value. With this purpose in mind, we will calculate the Network-Value-Metcalfe's Law ratio.

$$NVML = \frac{Market\ Capitalization}{ML_{value}}$$

Considering the volatility of the crypto asset market, and more specifically BTC, a moving average will be used in an attempt to smooth the ratio.

$$NVMLS = \frac{Market\ Capitalization}{MA(ML_{value})}$$

A similar approach and thought process will be applied using Odlyzko's law. Consequently, the NVOL ratio will be calculated (also applying a moving average).

$$NVOL = \frac{Market\ Capitalization}{OL_{value}}$$

$$NVOLS = \frac{Market\ Capitalization}{MA(OL_{value})}$$

3.3.2.6 Cost of production model

The value of BTC will be estimated using the cost of production model proposed by Hayes (2015). The steps involved in this model are listed below:

- Calculate the expected average number of bitcoins to be earned by miners on a daily basis.

$$\frac{BTC}{day} = \frac{\frac{\beta * \rho}{\delta * 2^{32}}}{sec_{hr}} * hr_{day}$$

Elements of this formula include β, which refers to block reward, ρ, the hashing power, and δ, the difficulty of the algorithm. Regarding units, β is expressed as BTC/block and δ as GH/block. As for the constants of this formula, sec_{hr} represents the number of seconds in an hour (3,600 seconds to be exact) and hr_{day} the number of hours in a day. Lastly, 2^{32} refers to “the normalized probability of a hash solving a block and is a function of the bitcoin algorithm” (Hayes, 2015, p.3). Since this probability is expressed in H, it must be converted to GH.

- Estimate the cost of mining per day.

$$E_{day} = \left(price\ per\ kWh * 24 * W\ per \frac{GH}{s}\right) * \frac{Hash\ power\ in \frac{GH}{s}}{1000}$$

- Estimate BTC USD.

$$p^* = \frac{Cost\ of \frac{mining}{day}}{\frac{BTC}{day}}$$

3.3.3 Estimating BTC USD using a VAR model

Reviewing the above valuation approaches will provide a solid foundation for understanding the underlying factors that drive BTC USD. As a result, the next logical step will involve building a VAR model using the variables explored throughout the research (if applicable) as inputs with a view to predicting BTC USD.

According to Medaka et al. (2019, p. 1142), VAR is a "multivariate forecasting algorithm that is used when two or more time series influence each other". Consequently, there are two basic requirements when building a VAR model:

- The model must consists of at least two time series (or variables).
- The selected variables should influence each other.

The motivation for using a VAR model is based on two key reasons. First and foremost, there are multiple variables influencing the value of BTC, with some of them showing interdependencies with BTC USD. As a result, a model such as a VAR algorithm is required to capture the simultaneous and potential interactions between them. Secondly, a model that account for both, short-term fluctuation and long-term patterns is imperative considering the high volatility of BTC USD, which is the case of the VAR model.

Furthermore, it has been proven that the VAR model "often provides superior forecasts to those from univariate timeseries models" and is particularly variable when describing and forecasting the dynamic behavior of time series in financial and economic contexts (Zivot and Wang, 2003, p. 383).

With a view to building a VAR model, the following steps will be performed:

Stationary analysis: assessment of the stationarity of the variables to be (potentially) included in the model using the Augmented Dickey-Fuller (ADF) test. In case of non-stationary variables, transform them into stationary. This step will ensure the stability of the relationships between the variables over time.

- Causality analysis: evaluate the causal relationships between the variables using the Granger causality test to determine which variables can be used to predict another and thus can be used as inputs.

- Variable selection: having evaluated the causal relationship between the variables, choose those that influence each other and can be used to predict one another.
- Arrange training and test datasets.
- Lag order selection: determine the optimal lag order for the VAR model using the Akaike Information Criterion (AIC).
- Train the model: train the VAR model using the training set using the selected variables and appropriate lag order.
- Forecast and evaluation: use the VAR model to generate predictions for the target variable (BTC USD) using the test set, rollback the stationary transformations and evaluate the performance using the mean absolute percentage error (MAPE), mean percentage error (MPE) and root mean squared percentage error (RMSPE).

4. DATA

4.1 Main data sources

Despite the astonishing amount of data available on crypto assets, according to Alexander and Dakos (2019) less than half papers on crypto assets since January 2017 employ correct data. As a result, choosing the right data sources is particularly relevant in crypto assets research. In addition, due to crypto markets operating non-stop, accessing the latest data is the crucial catalyst to ensuring the information is accurate and up to date.

Taking the above premises into account, Messari will be the main source of data throughout this research since it aggregates most of the trading activity of crypto assets and, thus properly describing and reflecting the features of the market as a whole (Vidal-Tomás, 2022). Data was imported from this source using a Messari API:

```
from messari.messari import Messari
import matplotlib.pyplot as plt
import pandas as pd
MESSARI_API_KEY = 'dzqN-ScKJaQgdswgxfI7KT6wWFUSxY5KWTn-
PO7+7EvfvnC+'
messari = Messari(api_key=MESSARI_API_KEY)
```

Because the focus of this research is the valuation of crypto assets, and more specifically BTC, the majority of the imported data consists of information regarding this cryptocurrency:

```
asset = ['bitcoin']
asset_metadata = messari.get_asset(asset_slugs=asset)
asset_metadata.head()
```

Unless specified otherwise, data and information employed throughout this research will be accessed using Messari and calculated using Python code. Even though Messari was the main database for this research, other sources include:

- Nasdaq
  Nasdaq (2013) was employed with a view to accessing the historical price of gold and calculating its returns to compare the volatility of crypto assets to that of gold.
- Coin Metrics
  Due to the complexity of calculating the NVRV ratio, it was imported from Coin Metrics (n.d.).
- U.S. Bureau of Labor statistics
  This database was accessed with a view to identifying the average cost of electricity in the US.

4.2 Exploratory analysis

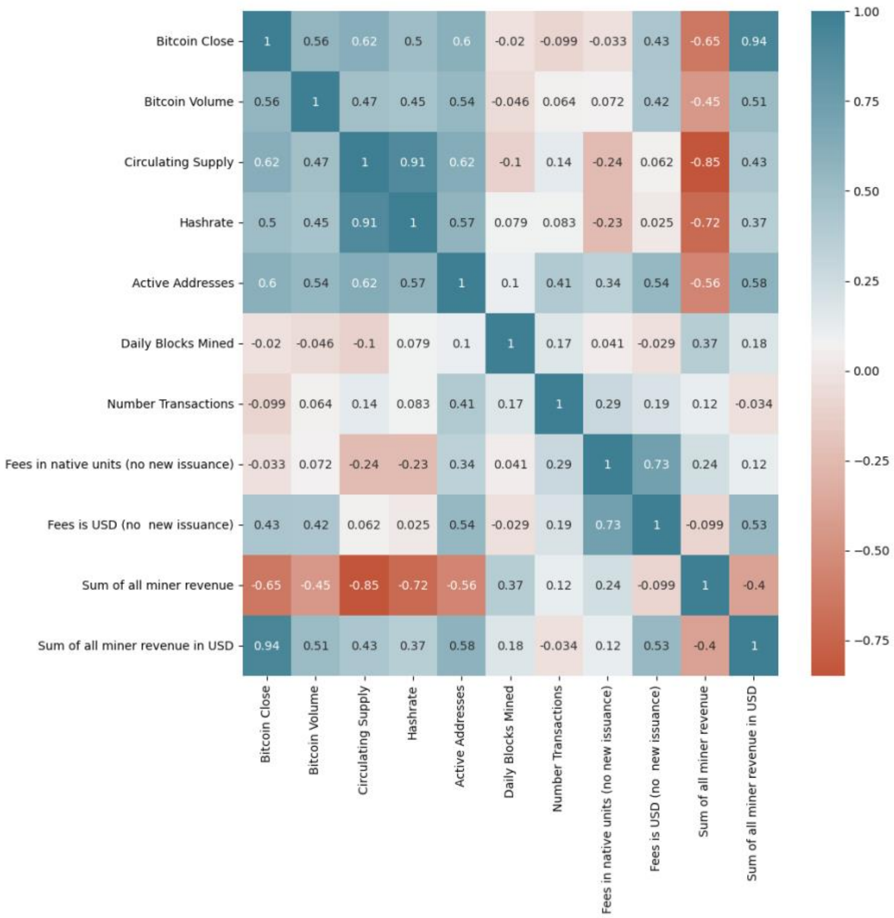
While all collected data is relevant for the present research, the aforementioned value drivers (listed in section 3.3.1) are the crucial catalyst to understanding the rationale behind the selected valuation approaches as well as to building the VAR model. Consequently, more emphasis must be placed on exploring these variables. The exploratory analysis conducted is documented in the appendix section.

5. ANALYSIS

5.1 The driving forces behind crypto assets' value is a controversial topic

With the purpose of identifying which variables are more strongly correlated with BTC USD, their correlations were calculated, which are represented in the below matrix (Figure 12). As it can be observed, metrics such as miners' revenue in USD, circulating supply, active addresses, volume of transactions in USD, and hashrate present the most correlation with BTC USD in descendent order. Surprisingly enough, the number of transactions appeared to have no correlation with BTC USD. This makes sense as the number of transactions is not meaningful enough unless their monetary value is also taken into account. Extrapolating these findings to other crypto assets, these variables possibly drive their value of and thus should be included in valuation approaches.

Figure 12: Correlation matrix.



Source: own elaboration.

5.2 Approaches to valuing crypto assets: a review of current methods

5.2.1 Total Addressable Market

According to Hougan and Lawant (2021), the total addressable market (TAM) model is the most widespread valuation approach in the context of crypto assets. Recapitulating, TAM is a market size variable that represents the overall revenue opportunity that is available to a product or service if the full market share was achieved. Since many people believe that BTC is a potential non-sovereign store of value (Hougan and Lawant, 2020), BTC's TAM will be estimated using the value of the gold market as a proxy.

As of 26th May 2023, the price of an ounce of gold is set at $1,944.3 (Nasdaq, 2013). Considering that 208,874 tonnes of gold have been mined up to the current date (World Gold Council, 2023), it could be estimated that these amount to roughly $13 trillion.

$$\begin{aligned}
&USD\ value\ of\ total\ market\ gold \\
&\quad = mined\ tonnes\ of\ gold * 32{,}000\,\frac{oz}{tonne} \\
&\quad * price\,\frac{gold}{ounze} \\
&\quad = 208{,}974\ tonnes * 32{,}000\,\frac{oz}{tonne} * \$1{,}944.3 \\
&\quad = \$13\ trillion
\end{aligned}$$

As previously mentioned, the total planned supply of BTC is 21 million. Returning to the concept of TAM, if BTC were to capture the total market of gold it would be valued at $13 trillion, which would imply a value of $619,136.3 per bitcoin. Following this trail of thought, if BTC was only able to capture 10% of the gold market, for instance, each bitcoin would be worth $61,913.6. The same reasoning applies to other calculations of the TAM. Taking into account that the current market capitalization of BTC amounts to $513 billion as of 26th May 2023, its value only amounts to approximately 4% of the gold market.

One of the main advantages of this model is that it can be easily escalated. For instance, one could consider not only the gold market but also other markets that act like a 'store of value' such as the real estate market or negative yielding bonds. While simplicity is another benefit of this model, it is also one of its limitations. Hougan and Lawant (2021) argue that this valuation approach falls short in many ways. First of all, the variables it is based on are all assumptions, which makes it extremely complex to obtain an accurate estimate of the total addressable market. Furthermore, the TAM model assumes that the value of BTC derives from this crypto asset being a potential store of value but ignores other used it might have.

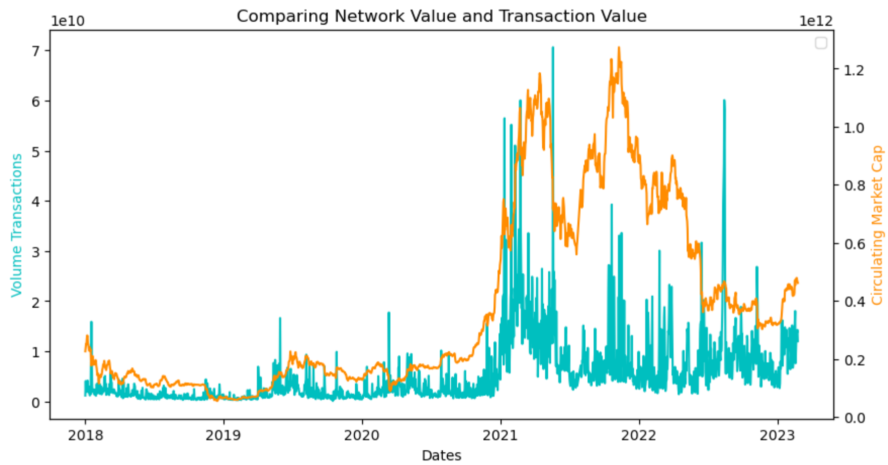
5.2.2 NVT Ratio

As aforementioned, the NVT ratio is quite interesting metric considering that it was the first that looked into network variables rather than financial in an attempt to adjust existing valuation methods to crypto assets' nature.

$$NVT = \frac{Network\ Value}{Daily\ transaction\ volume}$$

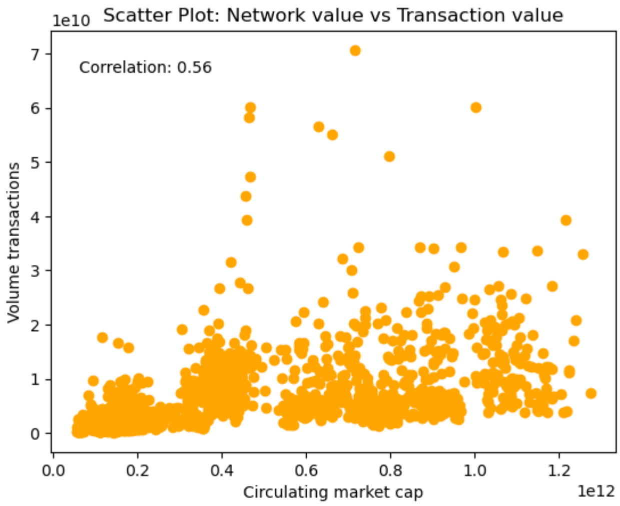
Prior to computing the NVT ratio, the relationship between network value and transaction volume will be analyzed.

Figure 13: Network value vs Transaction value.



Source: own elaboration.

Figure 14: Correlation Network Value & Transaction Value.

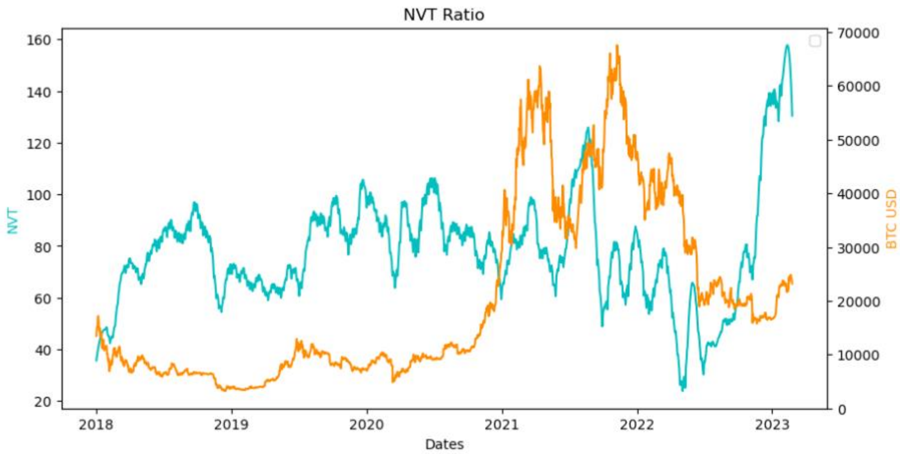


Source: own elaboration.

As it can be observed, there is a moderate positive relationship between the value that flows throughout BTC's network appears and the circulating market capitalization. Consequently, one could argue that transaction volume in USD might possibly be one of the factors driving the value of BTC.

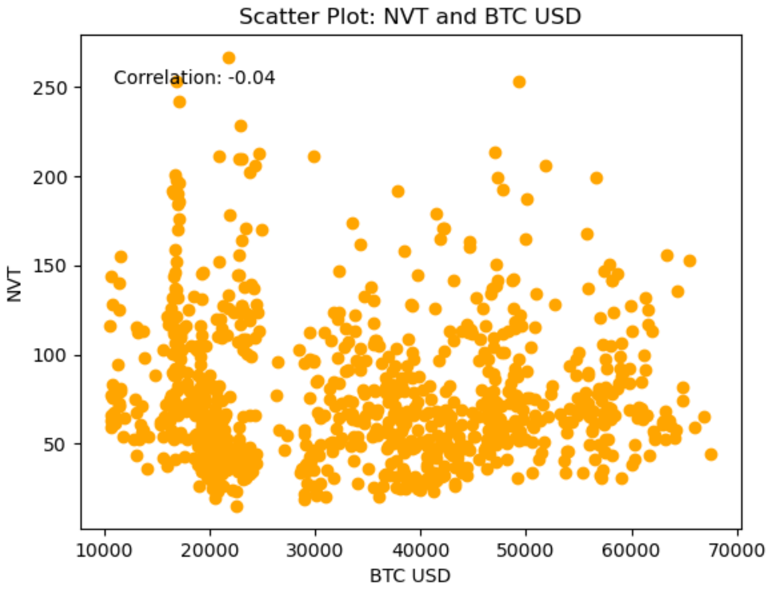
The following graph represents BTC USD and NVT ratio over the past five years. While NVT and BTC USD were relatively correlated throughout the second semester of both 2021 and 2022, they were heavily decoupled during the rest of the period of analysis.

Figure 15. NVT Ratio.



Source: own elaboration.

Figure 16: Correlation NVT and BTC USD.



Source: own elaboration.

Analyzing both figures, it is obvious that there is no correlation between NVT ratio and BTC USD, which suggests that the former is probably not a reliable metric for estimating the value of BTC. Reasons that might contribute to the NVT ratio not being a reliable valuation approach include the complexity of calculating on-chain USD transactions volume (Timo, 2020), which did to be a challenge when computing NVT. In other words, not only is calculating on-chain USD transactions volume quite a complex task but there are also several different approaches to calculating the latter, which can lead to different conclusions.

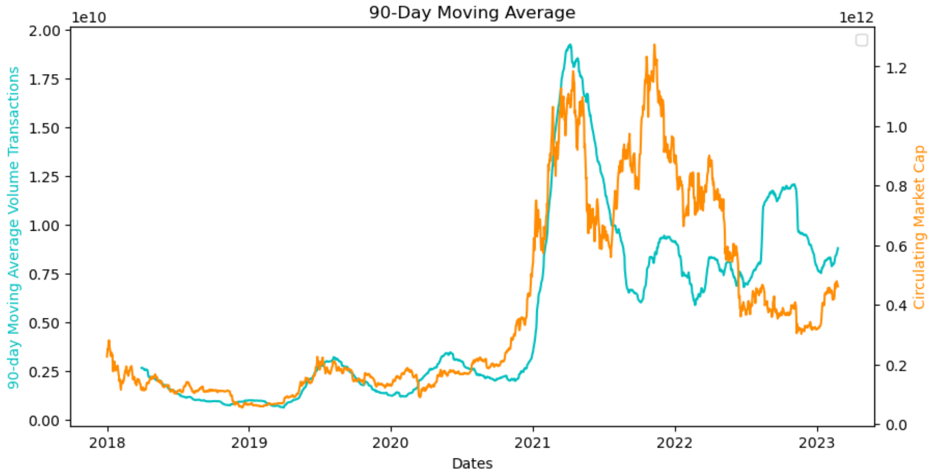
However, calculating on-chain volume transactions was not the only problem encountered with the NVT ratio. With a volatility of almost 52.4%, the NVT ratio is highly volatile, making it a difficult valuation approach to apply (Yang and Fantazzini, 2022).

Consequently, Kalichkin (2018) came up with the NVTS ratio, which added a 90-day moving average in an attempt to tackle NVT's volatility.

$$NVTS = \frac{Network\ Value}{MA_{Transaction\ Volume}}$$

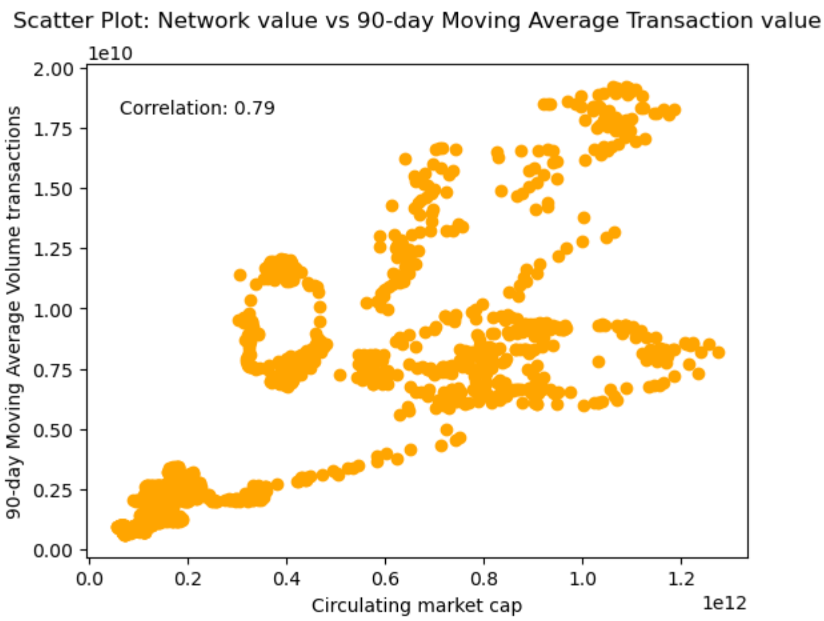
The 90-day moving average transaction volume is represented in Figures 17 and 18 along with the BTC's circulating market capitalization.

Figure 17: MA Volume Transactions & Circulating Market Capitalization.



Source: own elaboration.

Figure 18: Scatter Plot MA Volume Transactions & Circulating Market Capitalization.

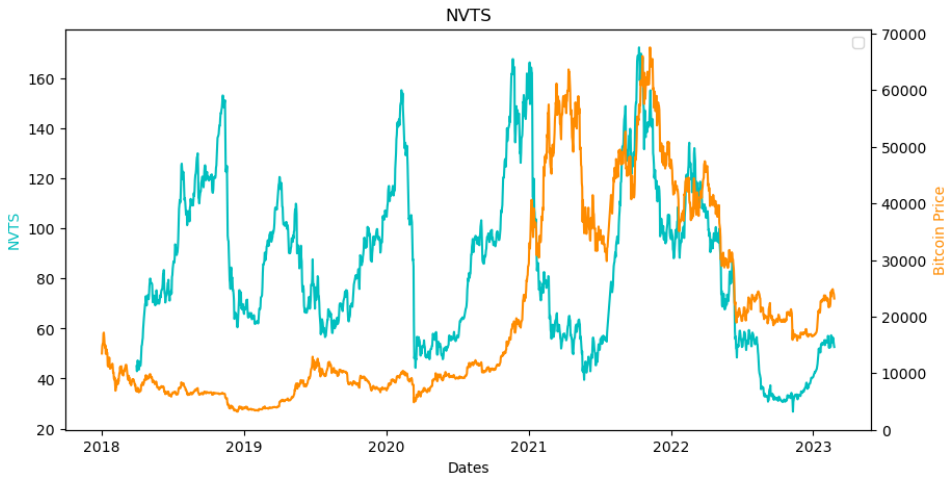


Source: own elaboration.

By looking at both figures, it is evident that the 90-day moving average transaction volume is much smoother than the transaction volume represented in Figure 13.

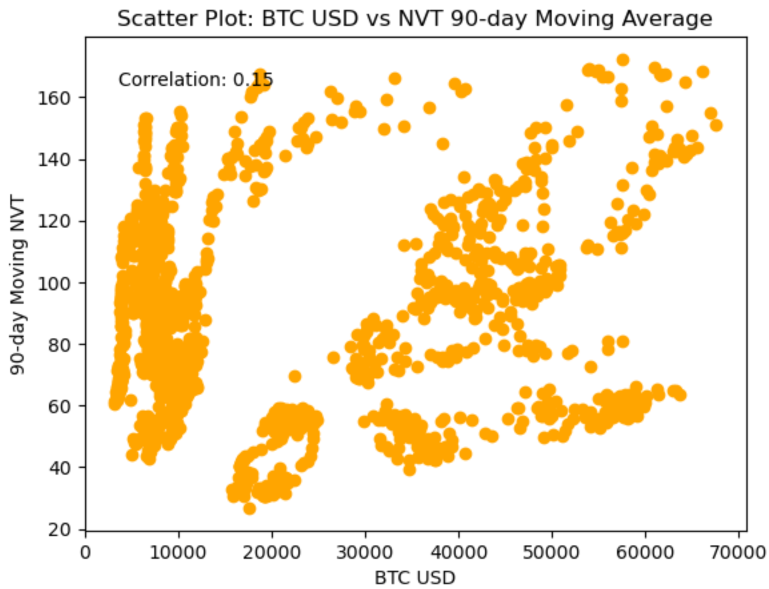
Furthermore, a stronger correlation between both parameters is achieved, which might indicate a better proxy for BTC USD.

Figure 19: NVTS ratio.



Source: own elaboration.

Figure 20: Scatter Plot NVTS and BTC USD.



Source: own elaboration.

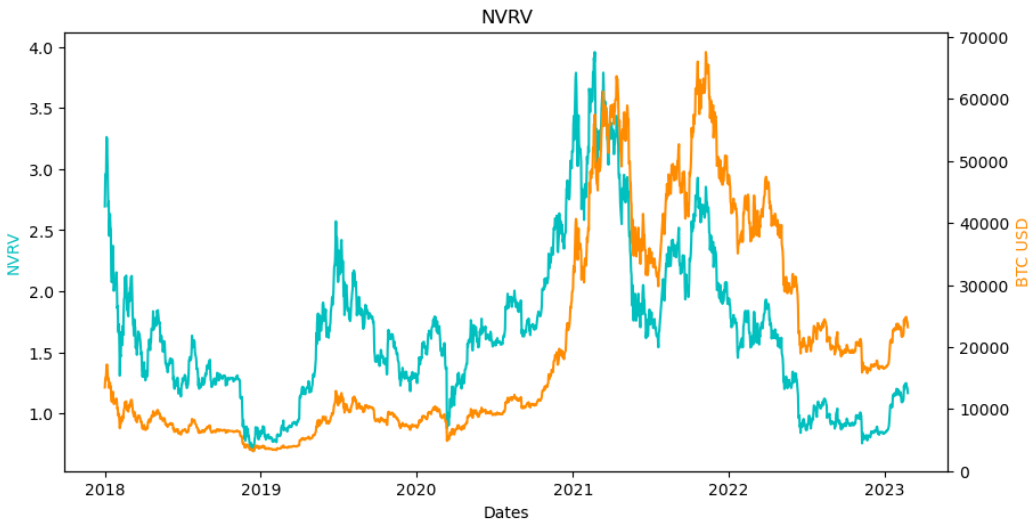
Even though significant volatility is still observed in the NVTS ratio (Figures 19 and 20), it shows lower volatility compared to the NVT ratio. More in detail, the NVTS ratio has a volatility of 38%, while the NVT ratio has a volatility of 52%. Furthermore, the correlation between the NVTS ratio and BTC USD is still low but higher compared to the NVT ratio, which might suggest that the former is a better proxy for BTC USD.

Other adaptations of the ratio include the Network-Value-Realized-Value ratio which was developed by Puell (2018) and accounts for lost coins and coins used for "hodling". The formula is as follows:

$$NVRV = \frac{Network\ Value}{Realized\ value}$$

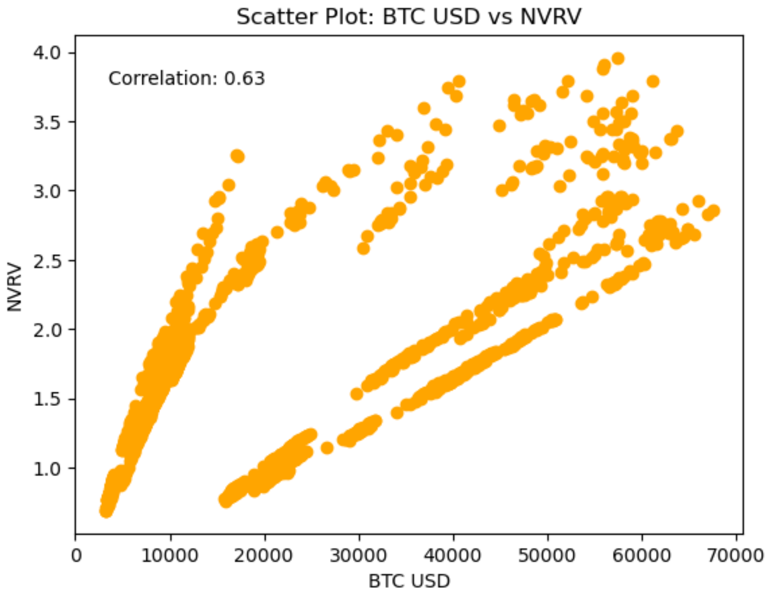
$$Realized\ value = \sum_i Last\ trade\ price\ of\ each\ coin$$

Figure 21. NVRV Ratio.



Source: own elaboration.

Figure 22: Scatter plot NVRV and BTC USD.



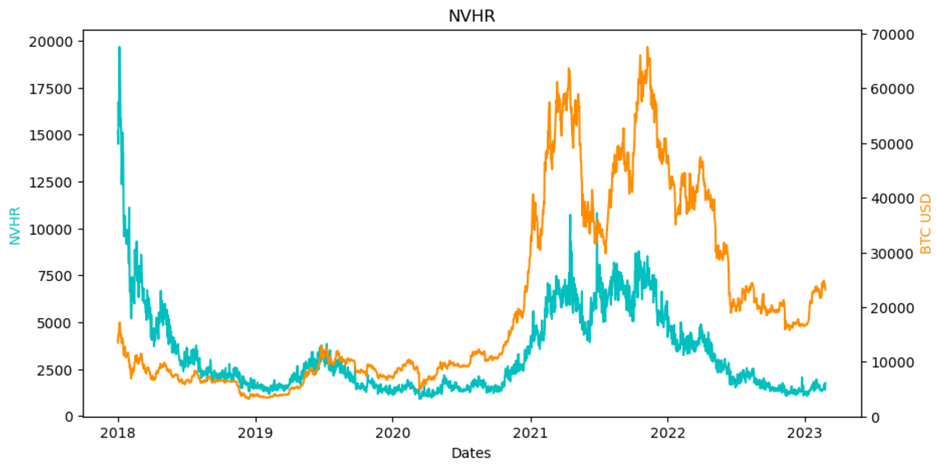
Source: own elaboration.

As it can be observed, NVRV is the ratio that presents the strongest correlation with BTC USD so far in spite of being quite decoupled during the first years of the period of analysis. Furthermore, it also manages to smooth transaction volume, with a volatility of 39%.

Another adaptation of the NVT ratio that includes cost metrics is the Network-Value-Hashrate ratio, which was explored by Yang and Fantazzini (2022). This ratio essentially measures the relationship between the network value and the hashrate and is commonly used to assess the efficiency and resilience of the network.

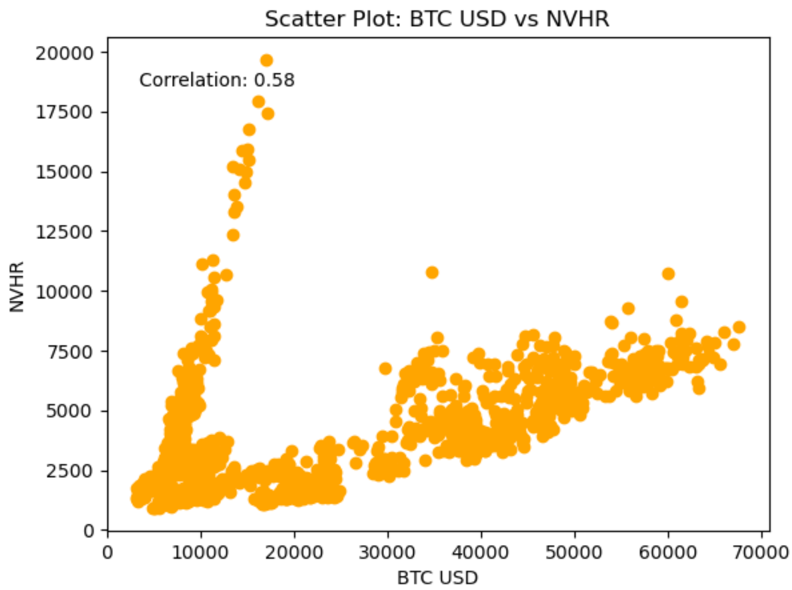
$$NVHR = \frac{Network\ Value}{Hash\ rate}$$

Figure 23. NVHR Ratio.



Source: own elaboration.

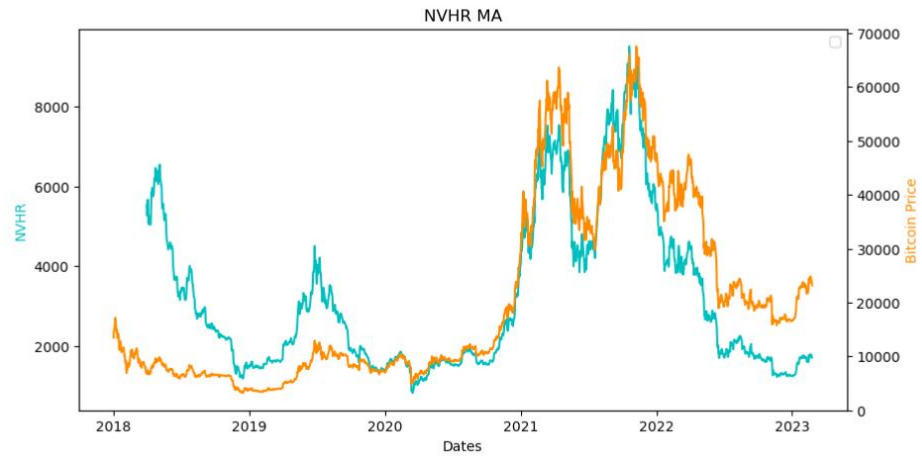
Figure 24: Scatter plot BTC USD and NVHR.



Source: own elaboration.

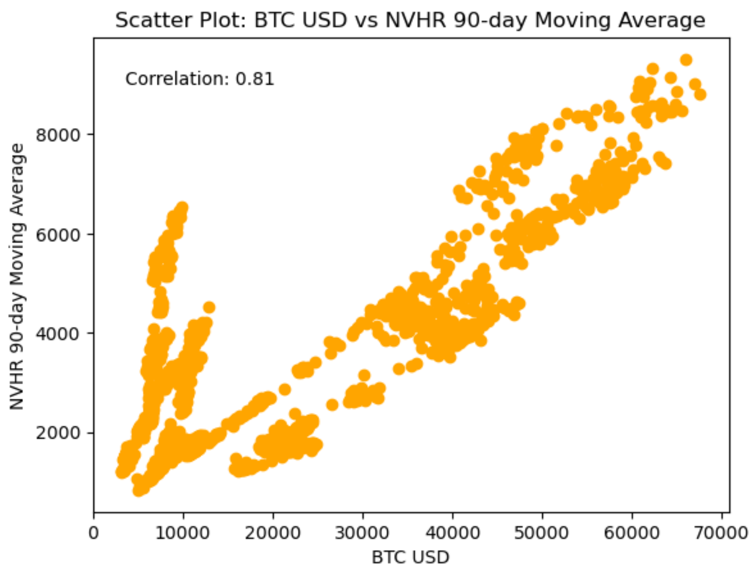
Even though the NVHR ratio and BTC USD show a moderate positive correlation, the former fluctuates significantly. In fact, the NVHR ratio ranges from a minimum of 916 to a maximum of approximately 19700 throughout the period analyzed and has a volatility of 70%. Considering the similarity in similar patterns and behavior between the NVHR ratio and BTC USD, the former could potentially become a valuable input to take into account when estimating the value of BTC. Consequently, attempts to reduce its volatility were made by using the moving average of the daily hash rate (Figure 25).

Figure 25. NVHR 90-day Moving Average.



Source: own elaboration.

Figure 26: Scatter Plot BTC USD and NVHRS.



Source: own elaboration.

As seen in Figure 26, there is a strong correlation between the NVHRS ratio and BTC USD, suggesting that the former has the potential to effectively track BTC and can thus serve as a valuable input when estimating the value of BTC. Even though the NVHRS ratio shows the stronger correlation with BTC USD so far (0.81 of correlation), it still shows significant volatility. In fact, the NVHRS ratio only managed to decrease volatility from 70% to 62%.

The above leads us to the conclusion that there are several valuation approaches deriving from the NVT, though none of them are academically recognized. Since some of these adaptations show a strong correlation with BTC USD and have the potential to effectively track, the next step would be to further investigate how they could be improved to better reflect the value of crypto assets.

5.2.3 Stock-to-flow

Recapitulating, the stock-to-flow expresses the relationship between the value of BTC and the amount of new bitcoin minted on a yearly basis, thus reflecting the idea of BTC USD being driven by scarcity. The stock-to-flow ratio is calculated as follows:

$$Stock-to-flow = \frac{Stock}{Flow} = \frac{Circulating\ supply\ Bitcoin}{Annual\ flow\ of\ production\ bitcoins}$$

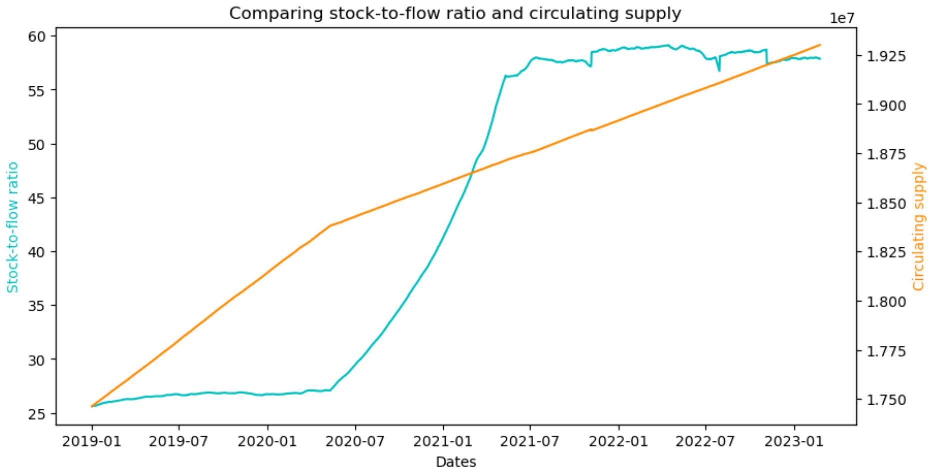
As of 26th May 2023, the current circulating supply in native units and annual flow of BTC are approximately 19.38 million bitcoins and 0.34 million bitcoins respectively[2]. Applying the above formula, we derive to the conclusion that the SF of BTC almost reaches 57.

$$Stock-to-flow = \frac{Stock}{Flow} = \frac{19.38\ million}{0.34\ million} = 57$$

As it can be observed when looking at Table 2, BTC is the second highest in terms of scarcity compared to the rest of assets analyzed. This suggests that, according to the stock-to-flow model, BTC will theoretically maintain its monetary value throughout time. With a view to analyzing the evolution of BTC in regard to the stock-to-flow ratio, the following graphs were plotted.

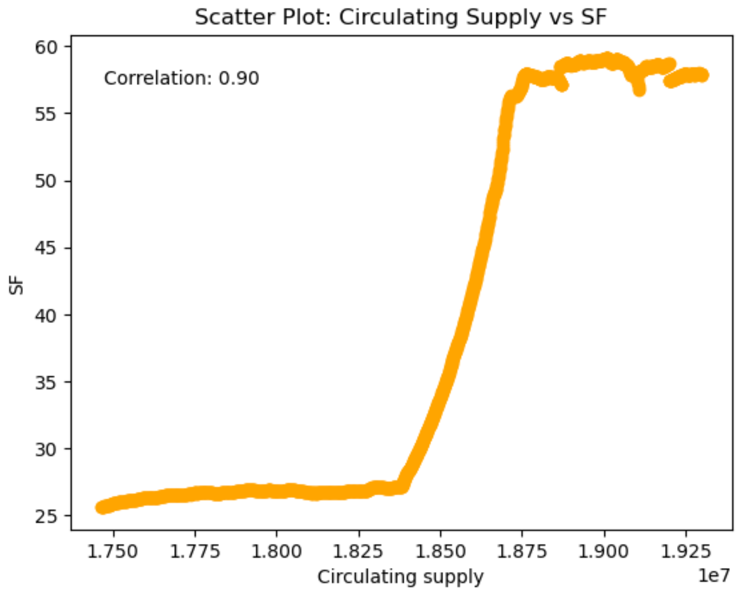
[2] Data accessed from Python using code.

Figure 27: Stock-to-flow ratio and circulating supply BTC.



Source: own elaboration.

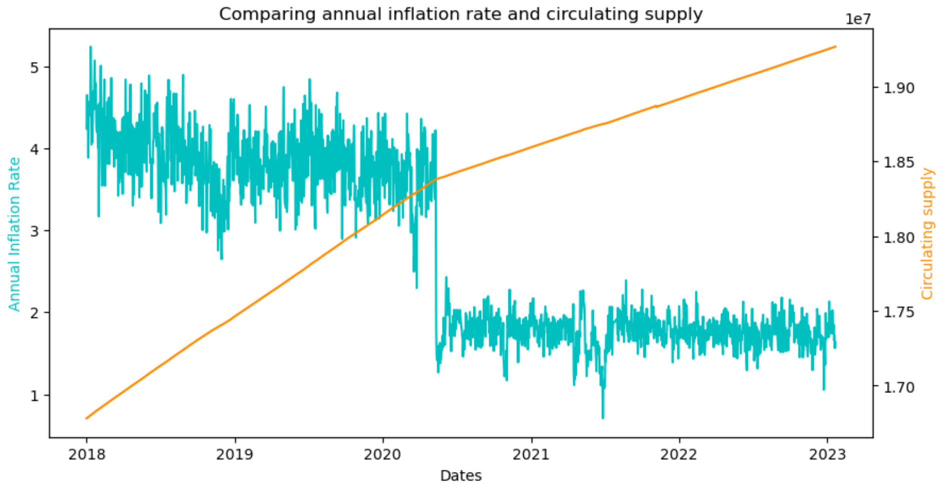
Figure 28: Scatter Plot Circulating Supply and SF.



Source: own elaboration.

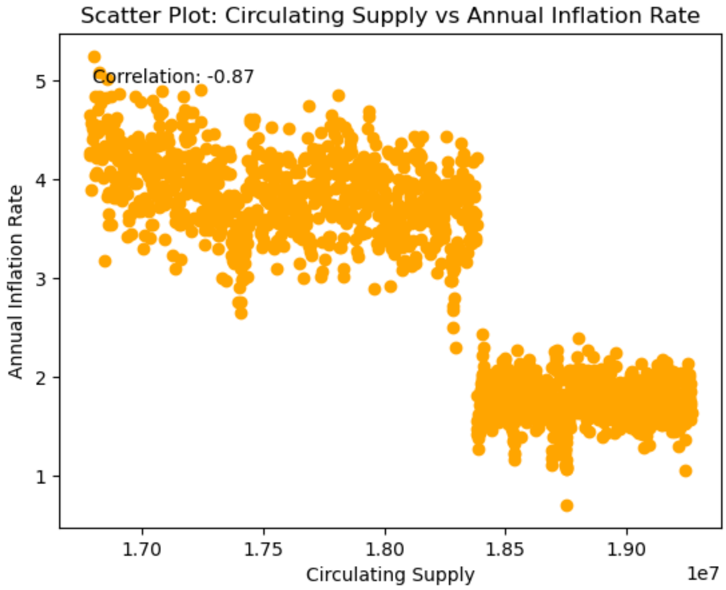
When looking at Figure 27, it is evident that there is a sharp increase in the stock-to-flow ratio when the rate of supply decreases. In this context, understanding the concept of halving is imperative. As mentioned in previous sections, every 210,00 blocks created the supply rate of BTC is cut to half, which decreases the annual flow of bitcoins and thus increases the SF ratio. This relationship is more clearly observed in Figure 28, with SF and circulating supply showing a strong correlation of 0.9.

Figure 29. Annual inflation rate and circulating supply.



Source: own elaboration.

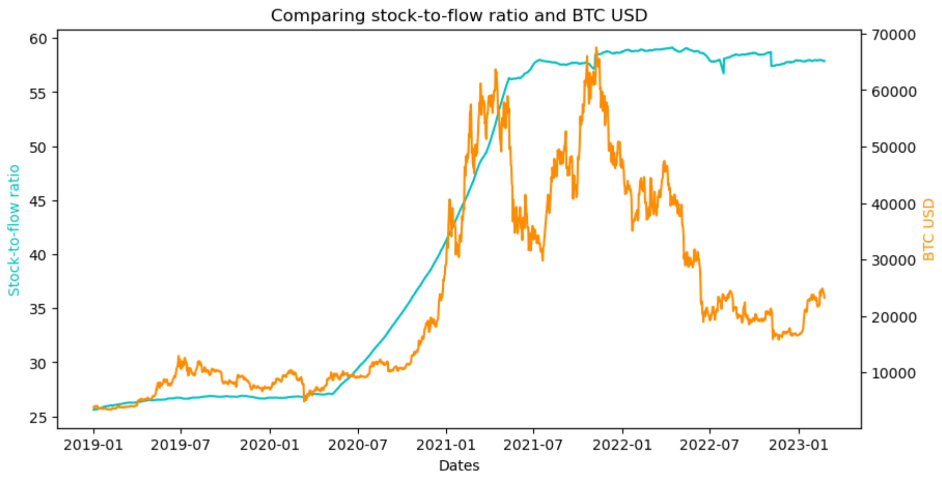
Figure 30: Scatter Plot Circulating Supply and Annual Inflation Rate.



Source: own elaboration.

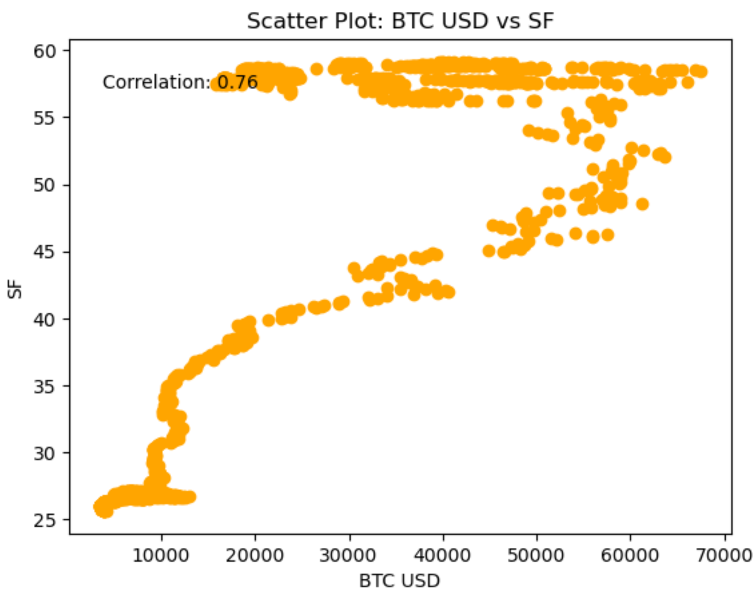
Figure 29 shows how, as the circulating supply increases over time, the supply growth rate diminishes. The last halving took place on 11th May 2020 which explains the sharp drop in the annual inflation rate. The latest halving also elucidates why, in Figure 27, there is a dramatic increase in the stock-to-flow ratio. As a result, it would be valid to conclude that the stock-to-flow ratio largely depends on the so-called halvings, which take place every four years approximately. With a view to analyzing the relationship between SF and BTC USD, the following graphs were plotted.

Figure 31. Scarcity drives value.



Source: own elaboration.

Figure 32: Scatter Plot SF and BTC USD.



Source: own elaboration.

Analyzing the above graphs, Figure 31 best reflects the concept of scarcity driving the value of BTC. As it can be observed, following the halving that took place on 11th May 2023, there was an increase in both, the stock-to-flow ratio and BTC USD, revealing the importance of scarcity in BTC USD. In fact, both variables show a relatively strong correlation of 0.76.

Even though scarcity can be considered as a fundamental driver for BTC USD, the stock-to-flow ratio is overly simplistic since it assumes that scarcity is the only driver behind BTC USD. Consequently, it misses out on other factors that also drive the value of BTC and other crypto assets such as demand and size of the network.

Furthermore, taking into account that the annual flow of bitcoins decreases programmatically over time due to the so-called 'halvings', the stock-to-flow ratio will inevitably rise in the long-term, which can be deceiving to investors. In the end, although the stock-to-flow model has long been a subject of debate in the community of crypto users, its underlying limitations make it one of the least seriously considered valuation approaches (Hougan and Lawant, 2021).

5.2.4 Quantity theory of money

Following the methodology developed to estimate the value of BTC using the quantity theory of money, the first step will be to calculate velocity. Recapitulating, V is defined as the frequency at which a unit of crypto asset changes hands and is defined as follows:

$$V = (P * Q)/M$$

With the purpose of estimating velocity, M will be first calculated:

$$\begin{aligned} M &= BTC\ USD * circulating\ supply = (\sim 19.38\ million * \$26{,}617.49\ ) \\ &= \$513\ billion \end{aligned}$$

Since the daily average USD transaction value in 2022 was approximately \$11.99 million[3], we could derive that the annual total USD transaction value was \$4,376.35 million (P*Q) (calculated by multiplying the average daily transaction volume in USD times 365 days).

[3] Data accessed using Python code.

With M referring to the market capitalization the velocity of BTC can be calculated:

$$V = \frac{\$11.99\, million * 365\, days}{\$516\, billion} = 8.48$$

A velocity of 8.48 indicates that, in 2022, each bitcoin was exchanged a total of 8.48 times. As stipulated by Lamothe Fernández and Lamothe López (2020), this high velocity indicates that investors are not holding on to bitcoins but are rather transferring them, diminishing their purpose as store of value. On the other hand, a low velocity implies that bitcoins are being held as investments by crypto users, which suggests that investors gave positive expectations of the market.

Having done the necessary calculations, the equation of exchange will be re-arranged to attempt to estimate BTC USD in 2023:

$$P_u = \frac{P * Q}{V * Circulating\ supply}$$

So far, the daily average volume of transactions in USD in 2023 is $10.5 billion[4]. Extrapolating this figure to the rest of days of 2023, and assuming the crypto assets is open 24/7, the estimated total volume of transactions in USD will almost reach $3,835 million by the end of the year.

With a view to calculating circulating supply of BTC at the end of 2023, we multiply the average current rate of bitcoins being issued on a monthly basis in 2023 by the remaining months of the year. We then add the number of bitcoins to be issued throughout 2023 to the current circulating supply:

$$Circulating\ supply_{End\ 2023} = 19.38\, million + 955\, \frac{bitcoins}{month} * 7 = \sim 19.386\, million$$

[4] Data accessed from Python using code

Considering that the average velocity of BTC during the last seven years was approximately 5.24[5] and that the average current rate of bitcoins being issued in 2023 is 955[6] we derive the future BTC USD:

$$P_u = \frac{\$10.5\ billion * 365}{5.24 * 19.386\ million} = \$37{,}726.6$$

The implied price based on the quantity theory of money is $37,726.6, whereas the actual BTC USD as of 26th May 2023 is $26,617.49. Therefore, the implied price exceeds the actual price by 40%, which is quite a significant deviation.

Considering how widely discussed this valuation approach is in the crypto asset market it is not surprising that several crypto researchers and investors have questioned its ability to properly reflect their value.

For instance, according to Hougan and Lawant (2021) one of the main challenges of this valuation model is estimating velocity, which is quite a complex task due to its high volatility. Such high volatility can lead to dramatic changes in the valuation of crypto assets, which can perhaps explain the 40% difference between the implied and actual BTC USD.

Other authors such as Cachanosky (2019) have noticed another limitation to this valuation approach. This crypto researcher argues that, over time, the adoption rate of BTC will inevitably keep increasing. Although the increase in adoption leads to a higher volume of transactions it also implies a larger shortage of supply, since in the case of BTC the latter programmatically decreases over time. This disequilibrium might further impact the applicability and accuracy of the model.

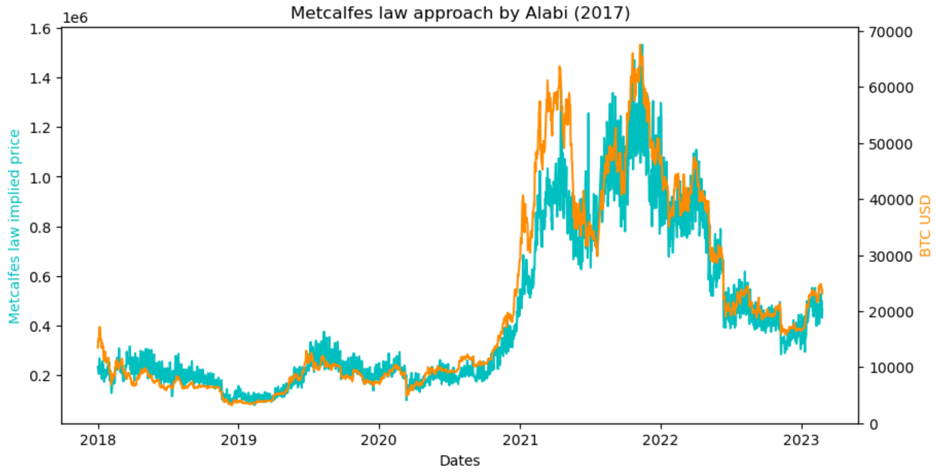
5.2.5 Active addresses

[5] Data accessed from Python.
[6] Data accessed from Python.

Similar to the NVT ratio, the Network-Value-Metcalfe's Law Ratio will be used to assess whether BTC USD has surpassed or fallen below the value implied by Metcalfe's law.

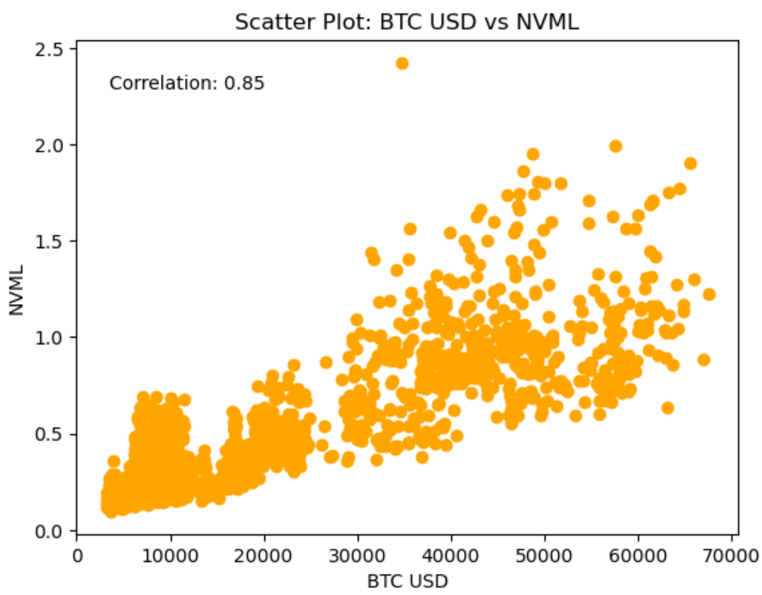
$$NVML = \frac{Market\ Capitalization}{ML_{value}}$$

Figure 33. Alabi's approach to Metcalfe's law.



Source: own elaboration.

Figure 34: Scatter Plot BTC USD and NVML.



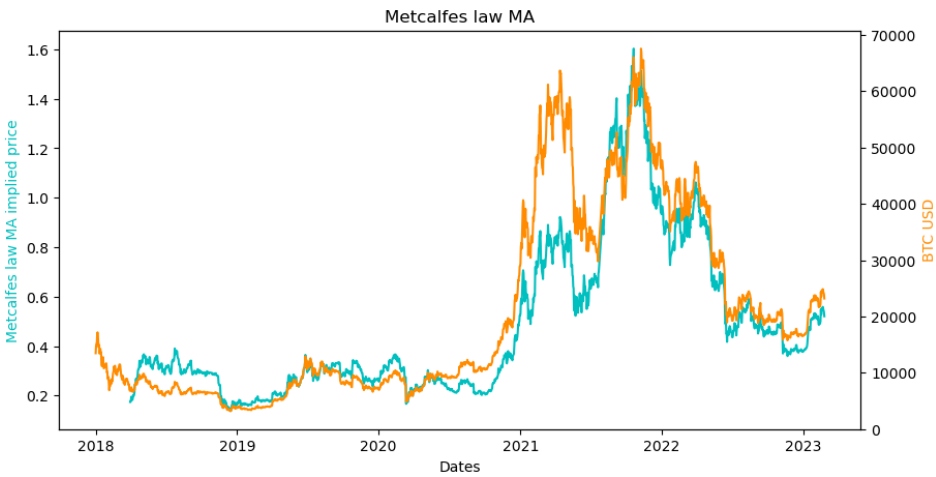
Source. own elaboration.

As it can be observed, there is a significantly strong correlation between Metcalfe's law and BTC USD, leading us to the conclusion that active addresses can be indeed used as a proxy for the value of a network. Indeed, this valuation approach has been widely accepted within the crypto asset community.

Nevertheless, and as with any valuation approach in the context of crypto assets, there are a few limitations to it. Due to the volatility of the market, the NVML also shows high volatility (70%). Consequently, a moving average will be used to smooth the above ratio:

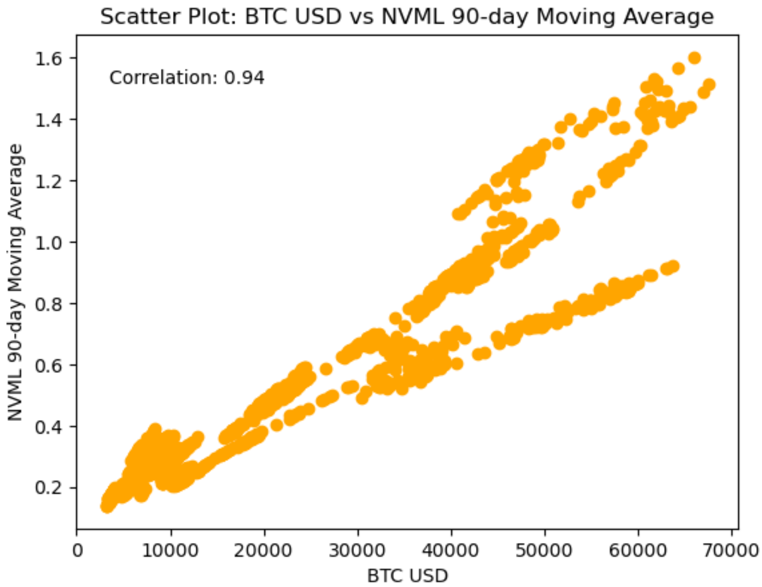
$$NVML = \frac{Market\ Capitalization}{MA(ML_{value})}$$

Figure 35. Metcalfe's law using a 90-day moving average.



Source: own elaboration.

Figure 36: Scatter plot NVMLS and BTC USD.



Source: own elaboration.

After applying a moving average of 90 days, the volatility of the NVML ratio correlation with BTC USD did increase from 0.85 to 0.94. However, volatility was not as significantly reduced, as it dropped from 70% to 65%.

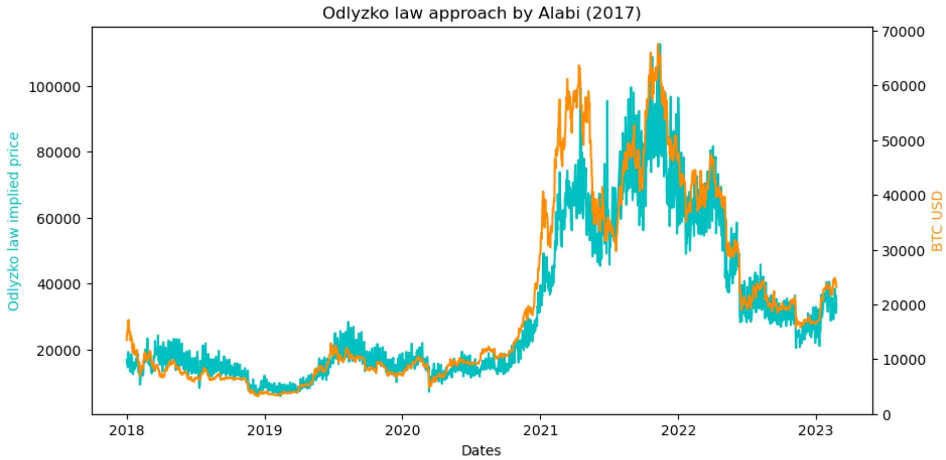
Even though Metcalfe's law has been proven to be a useful proxy for the value of BTC's network despite its volatility, there is another limitation inherent in it. As aforementioned, Metcalfe's law places equal weight on all active users and thus Odlyzko's law was developed.

$$OL_{Value} = n * \log{(n)}$$

Following the above thought process, the NVOL will be calculated:

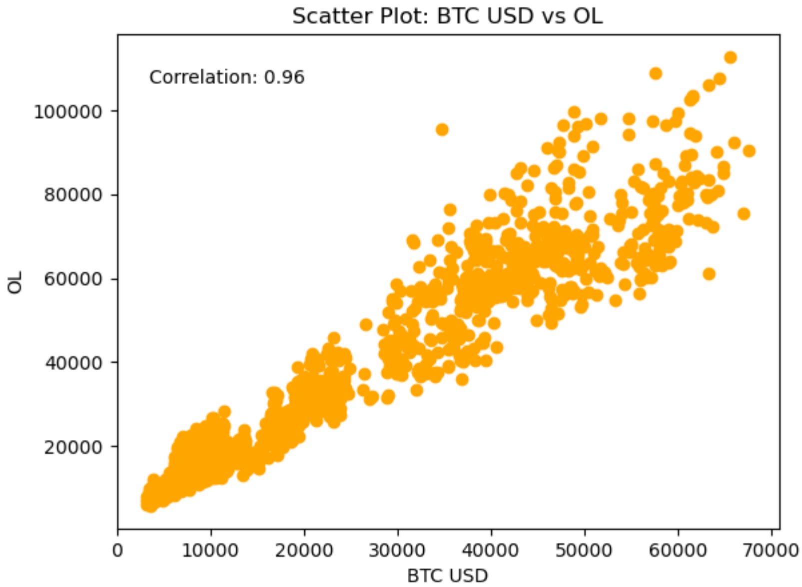
$$NVOL = \frac{Market\ Capitalization}{OL_{value})}$$

Figure 37. Odlyzko's law.



Source: own elaboration.

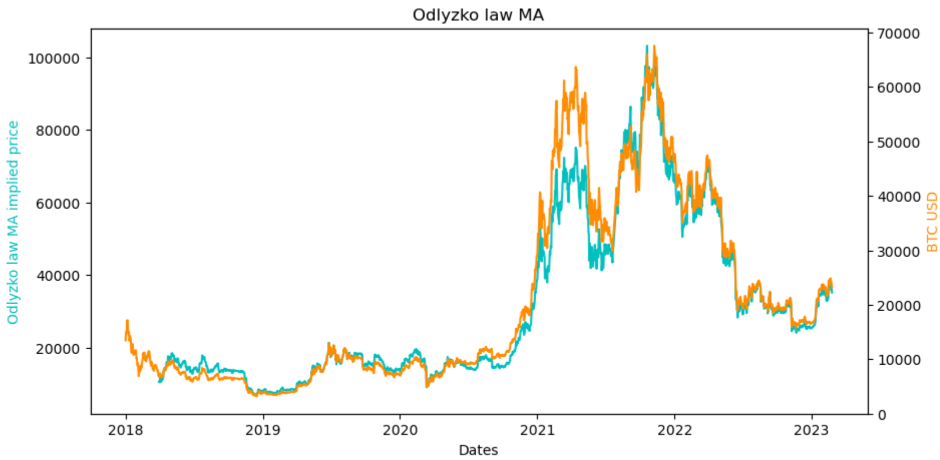
Figure 38: Scatter Plot BTC USD and OL.



Source: own elaboration.

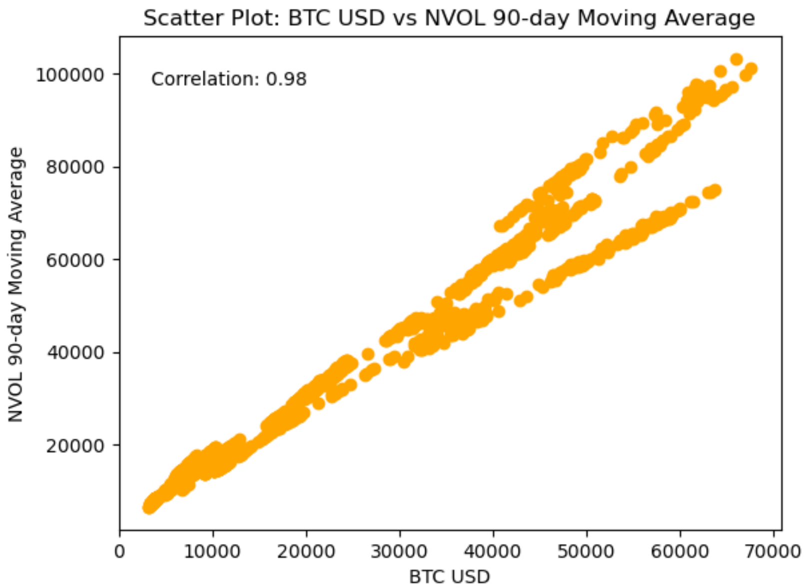
As it can be observed, NVOL closely follows BTC USD, with both metrics showing an astonishing correlation of 0.96. Even though one could argue that the NVOL can be an almost perfect proxy for the value of the network, it still faces the same challenges regarding volatility as Metcalfe's law (volatility of 74%). As a result, a moving average of 90 days was applied, leading us to a much less volatile ratio (Figure 39).

Figure 39. Odlyzko's Law using a 90-day Moving Average.



Source: own elaboration.

Figure 40: Scatter Plot BTC USD and NVOL 90-day Moving Average.



Source: own elaboration.

Even though the NVOL 90-day moving average has achieved an even higher correlation with BTC USD (correlation of 0.98), but it has not managed to decrease its volatility. In fact, volatility has only been reduced by 1%.

In brief, adaptations of the NVT ratio using active addresses as a proxy for BTC's underlying network value have shown promising results and should be further investigated.

5.2.6 Cost of production

The last valuation approached to be analyzed in this research is the 'cost of production' model. With a view to estimating the value of BTC, Hayes (2015) first applied the following formula to calculate the expected average number of bitcoins to be earned by miners on a daily basis.

$$\frac{BTC}{day} = \frac{\frac{\beta * \rho}{\delta * 2^{32}}}{sec_{hr}} * hr_{day}$$

Regarding the hashing power (ρ), as of 26th May 2023 the current total network hashrate is 327,455,000 TH/s. This data was accessed using the following code in Python:

```
metric = 'mining_stats'
response_data_df_market_data = messari.get_all_assets(asset_metric=metric,
to_dataframe=True)
response_data_df_market_data.head()
```

However, the hashing power for an Antminer S19 XP could be approximated to 140 TH/s (CoinWarz, 2023). Concerning the reward in native units per block, even though it started at 50 BTC, it has decreased to a current reward of 6.25 BTC (Abrol, 2023) due to halvings. The last element of the equation is the difficulty, which is set at roughly 5.12 trillion[7]. Applying the above formula, we get to the conclusion that the expected number of bitcoins earned by miners when employing 140 TH/s with a difficulty of 4.35 trillion is 0.0003435 BTC/day.

[7] Data accessed from Python using code.

The next step of the cost production model is to estimate the cost of mining per day, which is calculated as:

$$E_{day} = \left(price\ per\ kWh * 24 * W\ per \frac{GH}{s}\right) * \frac{Hash\ power\ in \frac{GH}{s}}{1000}$$

Before diving into further detail, there are two important factors to consider when calculating the cost of mining. First, the U.S has a hashrate share of 38% (Kassab, 2022), meaning that most of the BTC mining takes place in the latter country. Hence, the electricity price to be used in the formula will represent that of the U.S. Second, since the hashing power was previously calculated for an Antminer S19 XP, *W per GH/s* will represent the efficiency this model.

According to the U.S. Bureau of Labor statistics, the most recent average energy price for the U.S. is \$0.165 (U.S. Bureau of Labor Statistics, 2023) per kWh. Furthermore, the efficiency of an Antminer S19 XP can be calculated as:

$$Ef. = \frac{W}{\frac{GH}{s}}$$

Taking into account that the power and hashrate of an Antminer S19 XP are 3010W and 140 TH/s respectively, the efficiency of this model is 0.0215 W per GH/s. Applying the above formula, the average cost per day of mining is approximately \$12.91.

As aforementioned, in a competitive market the marginal cost of mining should equal the marginal product, and also the price (Hayes, 2015). Taking this equivalence into account, BTC USD could be estimated by simply calculating the following ratio:

$$p^* = \frac{Cost\ of \frac{mining}{day}}{\frac{BTC}{day}}$$

Nevertheless, the cost of production model does not exactly estimate what the theoretical BTC USD should be but rather establishes a lower bound for the market price. In other words, the p* represents a lower bound below which miners would incur in losses when mining and thus would remove themselves from the market. Taking the above into account, the lower bound for the market BTC USD would be:

$$p^* = \frac{Cost\ of \frac{mining}{day}}{\frac{BTC}{day}} = \frac{\$12.91}{0.00040416} = \$31{,}942.8.5/BTC$$

As of 26th May 2023, BTC USD stands at $26,617.5. Applying the theory proposed by Hayes (2015), since the market price is above the lower bound estimated by the model, miners are operating at a marginal profit and will not exit the market.

As it can be observed, several assumptions were made throughout the cost of production model. For instance, the electricity cost pf $0.168 per kWh was an estimate for the whole U.S. region and therefore did not take into account miners operating in other countries nor actual electricity prices for miners in the U.S. Furthermore, inputs such as the equipment's energy efficiency was estimated for just one model (Antminer S19 XP) and failed to capture the average mining efficiency mainly because getting a real picture of the distribution of different equipment amongst miners is not possible (Fantazzini and Kolodin, 2020). These assumptions make it extremely complex to obtain an accurate estimate of the underlying value of BTC.

5.3 VAR model to estimate BTC USD

Despite the benefits present in the reviewed valuation approaches, there limitation must also be acknowledge since they hinder their complete applicability. Consequently, relying on a single valuation approach might not yield optimal results when predicting BTC USD. However, the comprehensive review of valuation approaches and value drivers have provided a solid foundation for understanding the factors influencing BTC as well as its fundamental features and nature. Taking this into account, the next logical step is to take advantage of the learnings and build a VAR model to predict BTC USD.

As aforementioned, the first and foremost step is to assess the stationarity of the variables to be (potentially) included in the VAR model. In this context, the variables to be tested for stationarity include the following[8]:

Table 3: Variables to be tested for stationarity.

Variables
BTC USD
Circulating supply
90-day moving average transaction volume
NVRV
NVHR
NVHRS
SF
Annual inflation rate
NVML
NVMLS
NVOL
NVOLS

For the purpose of testing their stationarity, the Augmented Dickey-Fuller (ADF) test was employed using the following code[9]:

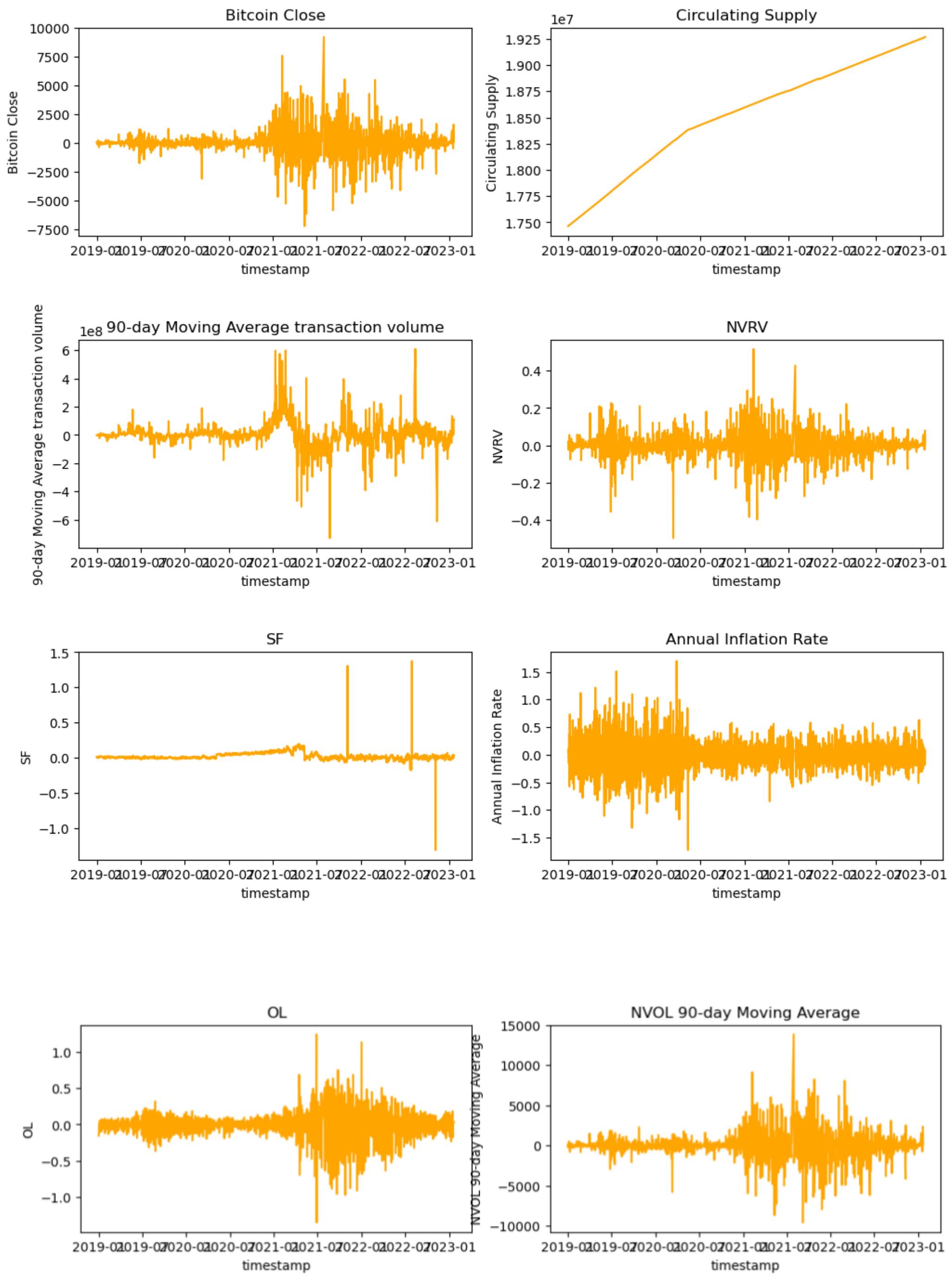
```
def check_stationarity(series):
    result = adfuller(series)
    p_value = result[1]
    return p_value
for column in dataset_cleaned.columns:
    p_value = check_stationarity(dataset_cleaned[column])
    print(f"Variable: {column}\tP-value: {p_value}")
```

When analyzing the results, only circulating supply had a p-value lower than 0.05, meaning that the latter was the only stationary variable of the dataset. As a result, the rest

[8] Since VAR assumes linear relationship between the variables, only those with relatively strong correlation with BTC USD have been selected.
[9] Dataset with all the variables is called dataset_cleaned.

of the variables had to be converted to stationary. A sample of the output of the transformations is shown in Figure 41.

Figure 41: Transformation of Variables to Stationary.



Source: own elaboration.

Having converted the variables to stationary, the next step will be testing the causal relationships between BTC USD and the rest of variables using the Granger causality test. In brief, this test evaluates whether including lagged values of a variable can help improve the prediction of the other variable. In the context of the present research, the Granger causality test will be conducted to analyze which of the variables listed in Table 3 can efficiently predict BTC USD.

```
variables = [col for col in dataset_cleaned.columns if col not in ["timestamp", "Bitcoin Close"]]
for var in variables:
    data = dataset_cleaned[['Bitcoin Close', var]].pct_change().dropna()
    print("")
    print(var)
    grangercausalitytests(data, maxlag=10)
```

From the set of variables analyzed, only the SF ratio showed a p-value lower than 0.05. Since the p-value of the SF stands at 0.0072, the null hypothesis is rejected (no significant evidence of causality). Therefore, it can be assumed that the lagged values of the SF ratio can significantly improve the prediction of BTC USD. Taking this outcome into consideration, the set of endogenous variables included in the VAR model will only consist of two time series, BTC USD and the SF ratio.

Once the dataset for the VAR model is assembled (1474 observations in total), the next step is to arrange the training and test datasets. Since we are dealing with time series, preserving the temporal order of the data is imperative. For this purpose, the variables will be sorted in ascendent order based on the dates. Lastly, the dataset will be split allocating 80% to the train set and the remaining 20% to the test set.

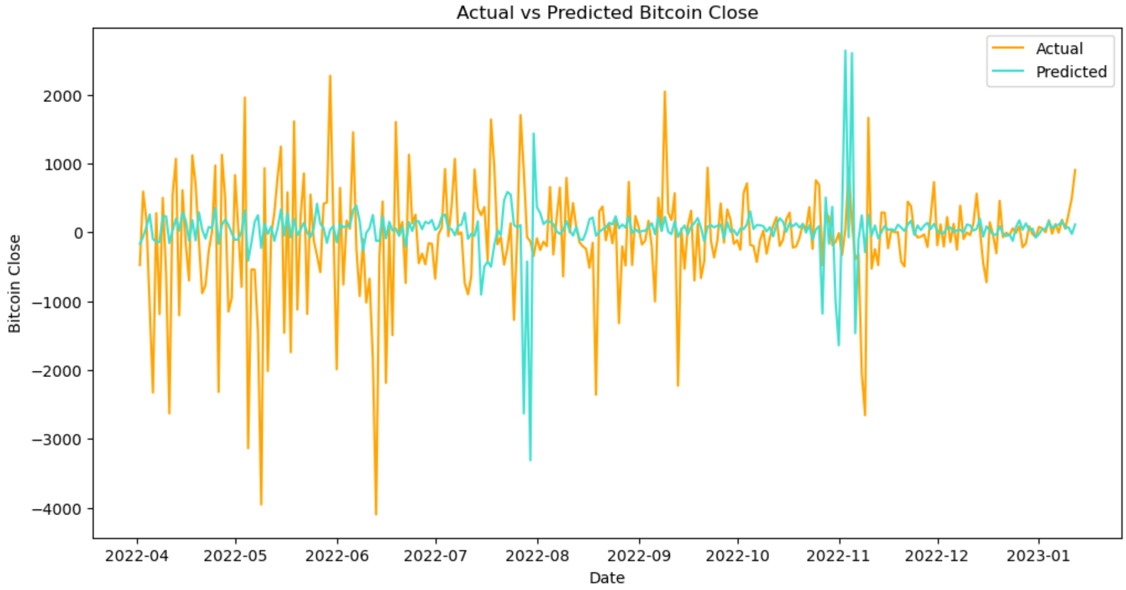
After preparing the training and test set, the next step requires determining the optimal lag order for the VAR model using the Akaike Information Criterion (AIC). The AIC essentially evaluates how well the model fits the data it was generated from. Consequently, a model with the lowest AIC is preferred. According to this test, the lowest AIC was achieved using a lag of 13 days, which will be the lag order used to train the model and make the predictions.

Having determined the appropriate lag order, the VAR model will be trained using 13 lags. Since this was the optimal number of lags, we will proceed with generating the BTC USD predictions for the test set. Since our model has been trained using 13 lags and our test set has 295 observations, it is necessary to incorporate a moving average to generate predictions for the whole test set.

```
# Number of optimal lags.
num_lags = 13
# Create a list to store the predicted values.
all_predictions = []
# Iterate over the 295 observations of the test set in chunks of 13 days.
for i in range(0, len(test_data) - num_lags + 1, num_lags):
    # Obtain the lagged values for each chunk
    lagged_values = test_data.iloc[i : i + num_lags].values
    # Generate predictions for each chunk.
    pred = result.forecast(y=lagged_values, steps=num_lags)
    # Include the predictions to the list.
    all_predictions.extend(pred)
# Create a new DataFrame to store all the predicted values.
df_forecast = pd.DataFrame(data=all_predictions,
index=test_data.index[:len(all_predictions)], columns=test_data.columns)
# Compare the predicted values with the actual values from the test set.
df_comparison = pd.concat([test_data[:len(all_predictions)], df_forecast], axis=1)
```

As it can be inferred from the code, both, the predicted and actual values of BTC USD were stored in the data frame “df_comparison”. With a view to providing a visual representation of the performance of the VAR model, the following graph was plotted.

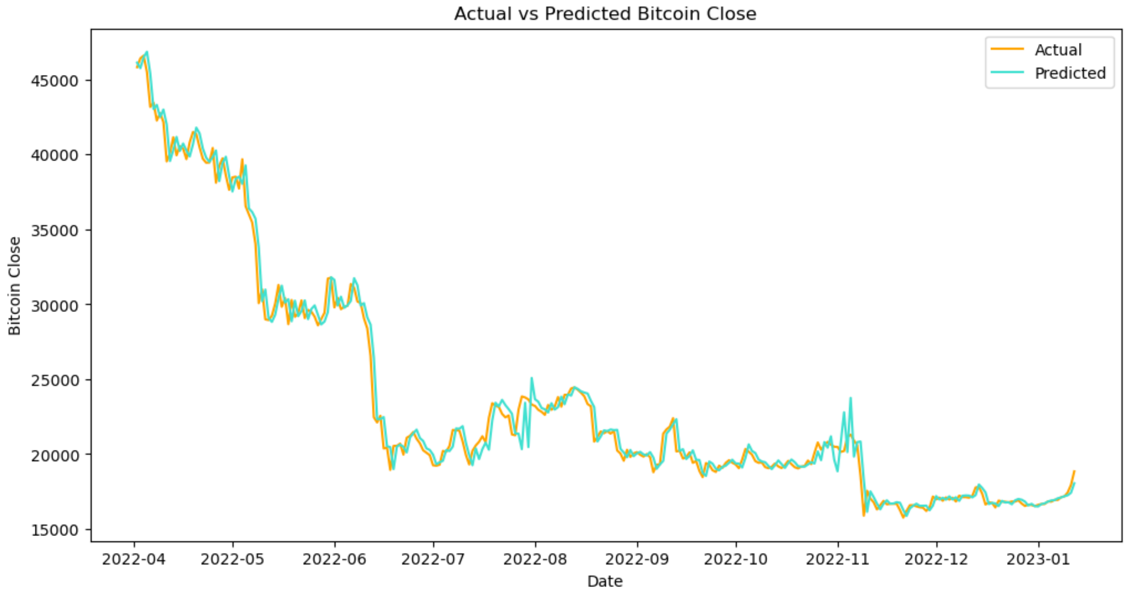
Figure 42: Stationary Predictions & Actual Values BTC USD.



Source: own elaboration.

However, the values represented in Figure 42 correspond to the values of the stationary variables. Consequently, the stationary transformation process will be inverted to obtain the original values of the variables.

Figure 43: BTC USD Predicted & Actual values.



Source: own elaboration.

At first glance, it appears that the VAR model has managed to capture the patterns of BTC USD, thus achieving to effectively track the latter. However, upon closer inspection, the predictions seem to be lagged by a few days. In other words, the model is not capturing the real-time movements and dynamics of BTC USD and is forecasting with a delay, which negatively impacts the accuracy of the model.

Furthermore, the predicted BTC USD values exhibit unexpected peaks at two instances, with one peak taking place during August 2022 and the second during November 2022. Prior to assessing the performance of the model, it is obvious that further refinement is needed to address the aforementioned issues and improve overall accuracy.

In order to evaluate the performance of the model, three metrics will be employed, including the mean absolute percentage error (MAPE), mean percentage error (MPE) and root mean squared percentage error (RMSPE).

Table 4: Performance metrics.

Performance metric	Value
MAPE	2.49
MPE	-0.55
RMSPE	3.76

Source: own elaboration.

The above metrics indicate a relatively low level of prediction error. For instance, a MAPE of 2.5 means that, on average, the predicted BTC USD values deviate from the actual ones by just 2.5%. The same reasoning is also applied to the MPE and the RMPSE. Consequently, it could be concluded that the VAR model performs relatively well.

Even though the above standalone figures are necessary to assess the accuracy of the model, it is imperative to compare the results with those obtained in other similar studies with a view to ensuring a more comprehensive performance evaluation. As a result, the MAPE generated by the VAR model will be compared against the MAPE of two analogous studies.

Table 5: Comparing MAPE across studies.

Result MAPE	Study
2.49	Present research

0.0249	Ibrahim et al. (2020)
2.57	Tosanwumi (2020)

Source: own elaboration.

Even though the MAPE generated by the VAR model of the present is relatively good, it falls short compared to the MAPE obtained by Ibrahim et al. (2020). However, when comparing it to the MAPE obtained by Tosanwumi it could be argued that the performance of the VAR model is in line with existing approaches. This suggests that, although there is room for further improvement and refinement, the VAR model is quite reliable when predicting the value of BTC.

5.4 Recommended next steps

The present section will provide an outline of the next steps to be followed with a view to building upon and improving the present work. In line with the main objectives of the research, further actions will be listed regarding both, the valuation of crypto assets and the refinement of the VAR model.

Throughout the research, the lack of consensus regarding crypto assets' valuation approaches was evident, suggesting that further research needs to be conducted in order to formally establish valuation methodologies. In this context, conducting additional research means delving deeper into the value drivers of crypto assets. Understanding what drives the value of crypto assets is the crucial catalyst to developing comprehensive and thorough valuation approaches.

Apart from identifying the main value drivers of crypto assets, the existing valuation approaches need to be further refined due to their limitations. Since the majority of issues that were identified when reviewing the valuation methodologies are associated with the high instability of the market, more advanced techniques beyond a moving average must be developed to tackle volatility.

Another limitation that was encountered is that valuation approaches tend to incorporate only one or two value drivers in their calculations, thus overlooking several other variables that also influence the value of crypto assets. As a result, developing valuation approaches that integrate as many value drivers as possible (if feasible) would be helpful in developing more comprehensive approaches.

Moving on to the second central theme of the research (the VAR model), suggestions primarily revolve around the set of endogenous variables included in the model. As aforementioned, multiple variables such as demand, supply or cost metrics, affect the value of crypto assets. However, the proposed VAR model includes the stock-to-flow ratio as the only predictor variable for BTC USD, an approach that, despite yielding favorable results, fails to include the multitude of factors that also affect BTC USD. Consequently, the model should be further refined by incorporating additional features to the dataset. Once a more comprehensive set of variables is achieved, other adjustments would include adapting the model architecture, determining the optimal number of lags etc.

6. CONCLUSIONS

Since the launch of BTC in 2009, the market of crypto assets has seen enormous growth, with thousands of different cryptocurrencies currently in existence. As technology continues to evolve, these assets will, without a doubt, play an increasingly important role in the global economy.

Taking the above into account, developing established and well-founded valuation approaches is imperative in a context where the market of crypto assets has experienced unprecedented growth. More specifically, properly valuing crypto assets is the crucial catalyst to enabling investors and traders to make informed decisions and better understand the potential opportunities and risks of investing in this market.

In spite of the importance of developing established frameworks for assessing the value of crypto assets, the analysis carried out throughout this research illustrates the lack of consensus regarding valuation methods. Discrepancies regarding how to appropriately value crypto assets have derived in the emergence of a vast array of valuation approaches, further complicating reaching an agreement on this subject. From adapting existing traditional methods to exploring new and disruptive approaches, researchers and academics have been attempting to develop successful valuation methodologies.

In this context, understanding the nature of crypto assets and thus, factors that drive their price, is the crucial catalyst to developing methods that best reflect their value. Following this line of thought, when valuing crypto assets investors should include other characteristics such as the whitepaper and developers to help estimate the potential of the project. The reasoning behind this is that much of the speculative value, although hard to estimate, can be derived from the above elements. For instance, people will have more faith in a crypto asset crafted by a talented and widely known team.

However, identifying crypto assets' value drivers is not enough. Since the issue regarding valuation approaches is rooted in the lack of consensus, reaching an agreement is crucial. In other words, collaboration between academics, industry professionals and researchers is imperative to gather different perspectives and foster the development of valuation methods with enough support from academia and industry stakeholders.

With a view to reaching an agreement on both, crypto assets' value drivers and valuation approaches, the VAR model proposed above should be refined by including a larger set of endogenous variables to identify how different factors influence the value of Bitcoin (and other crypto assets).

In conclusion, this research elucidates the need for academics and industry stakeholders to better comprehend where crypto assets' value stems from with a view to properly estimating the latter. Despite the lack of established approaches for the valuation of crypto assets, this research will serve as an overview of current methods to help the inquisitive derive meaningful ideas to make informed decisions and design suitable valuation approaches according to their needs. However, it's essential to keep in mind that investing in crypto assets can be highly speculative and comes along with significant risks. As a result, investors should conduct their due diligence and seek professional advice before investing.

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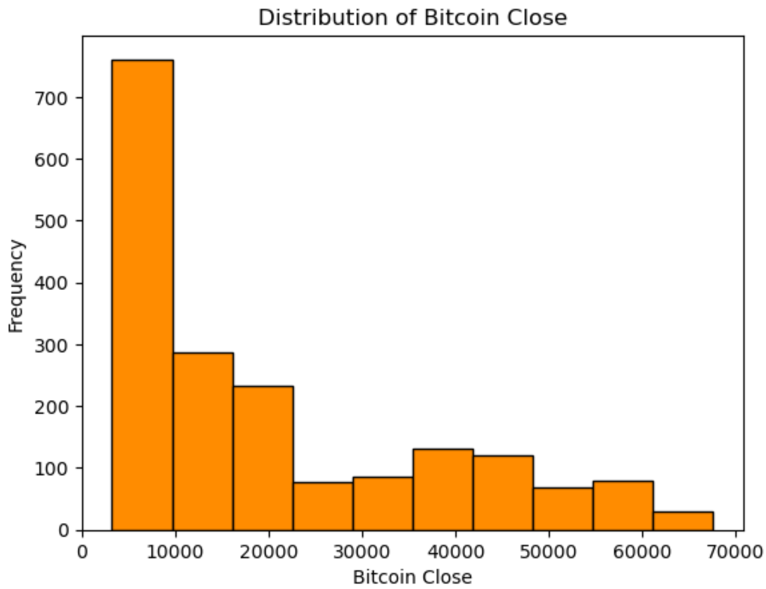
8. APPENDIX

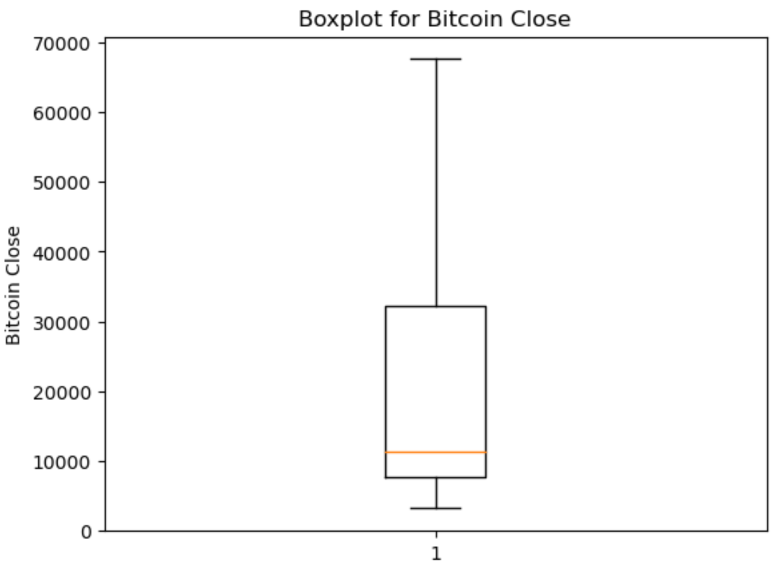
This appendix shows the exploratory analysis conducted for the value drivers listed in section 3.3.1.

Figure 44: Distribution BTC USD.



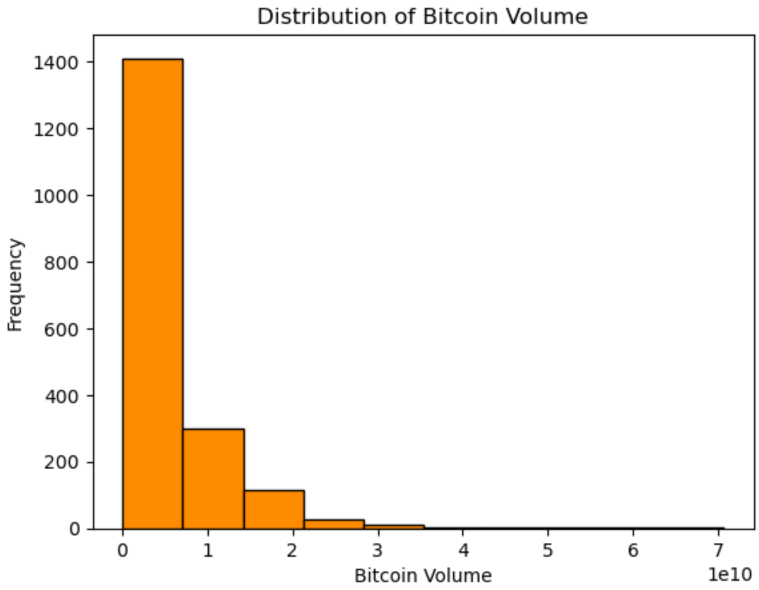
Source: own elaboration.

Figure 45: Boxplot BTC USD.



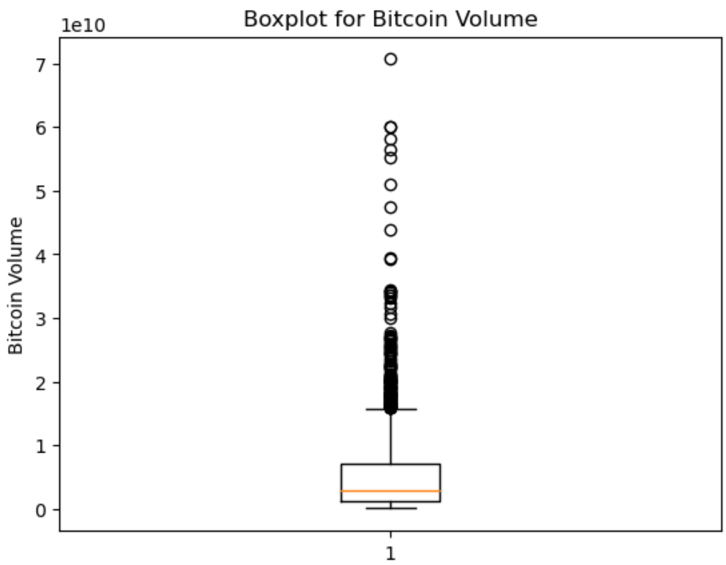
Source: own elaboration.

Figure 46: Distribution BTC Volume.



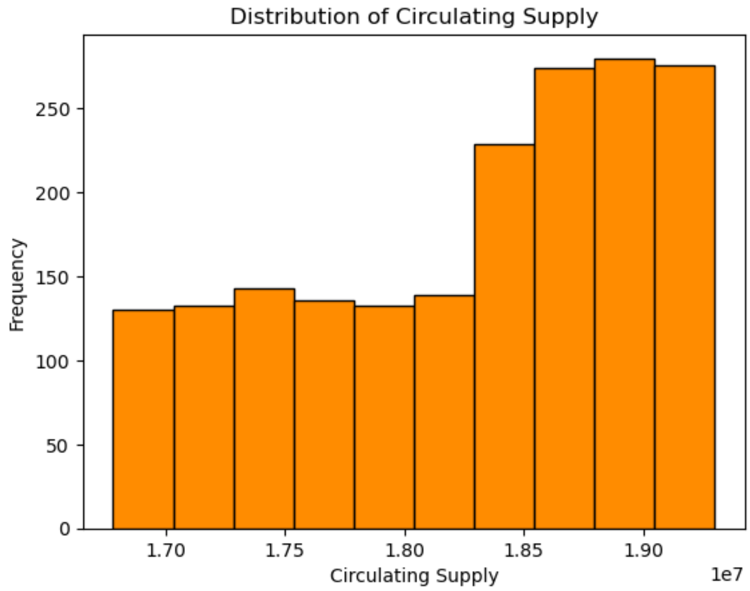
Source: own elaboration.

Figure 47: Boxplot BTC volume.



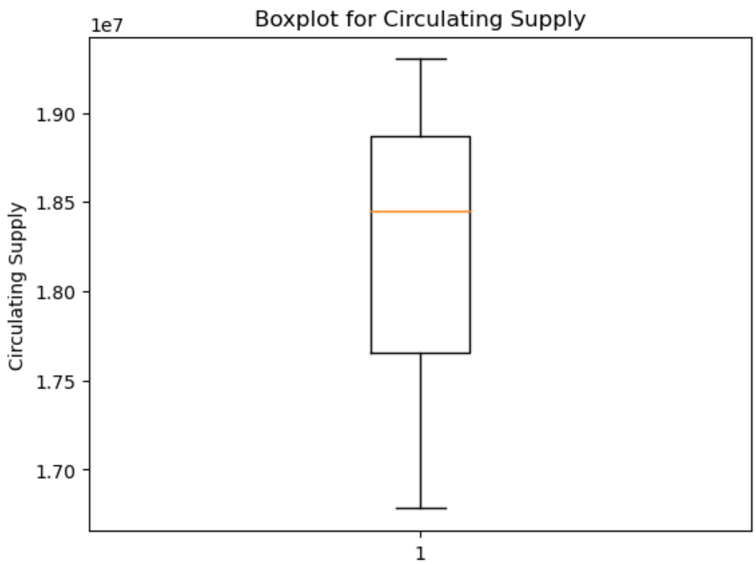
Source: own elaboration.

Figure 48: Distribution circulating supply.



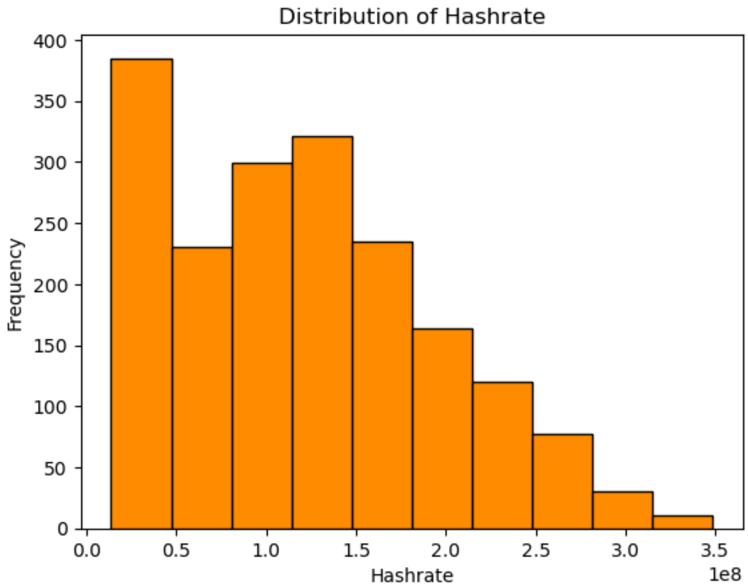
Source: own elaboration.

Figure 49: Boxplot Circulating Supply.



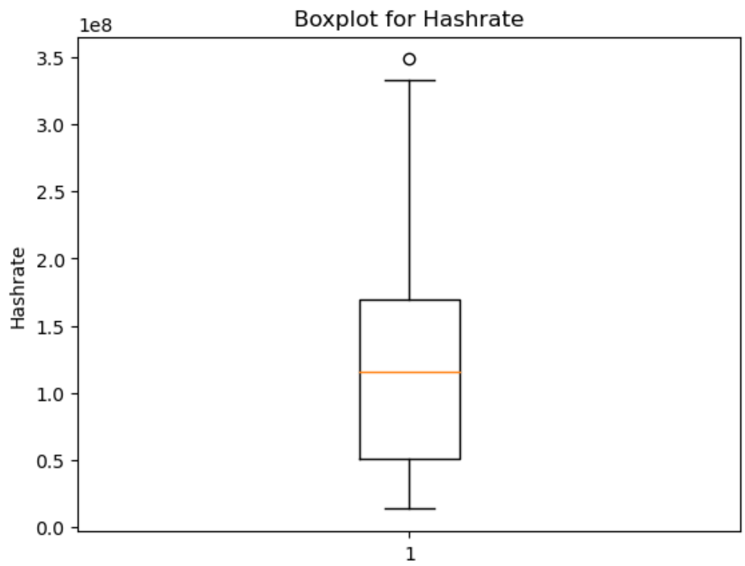
Source: own elaboration.

Figure 50: Distribution Hashrate.



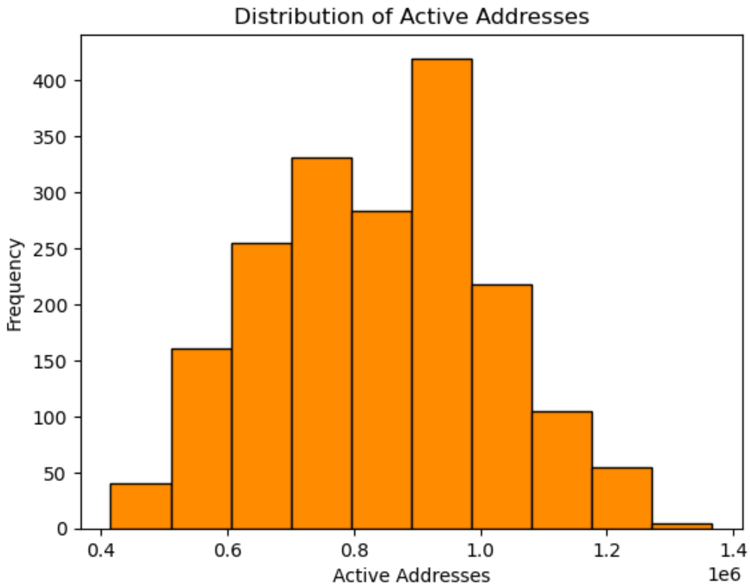
Source: own elaboration.

Figure 51: Boxplot Hashrate.



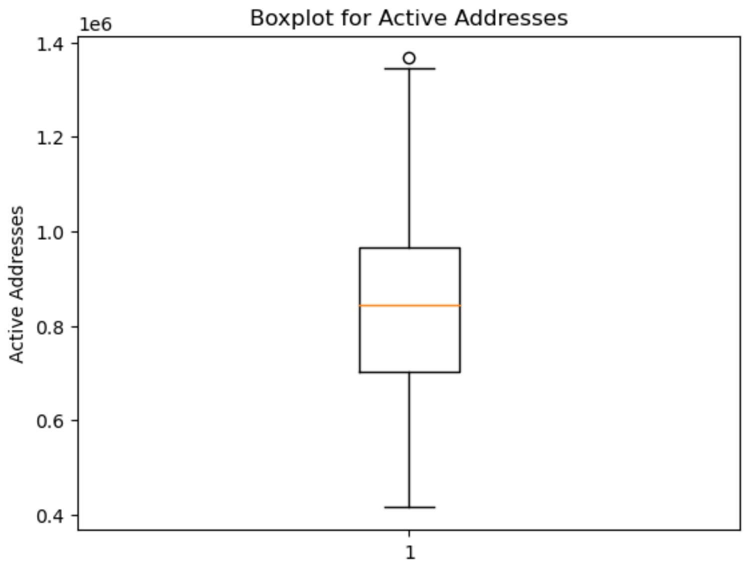
Source: own elaboration.

Figure 52: Distribution Active Addresses.



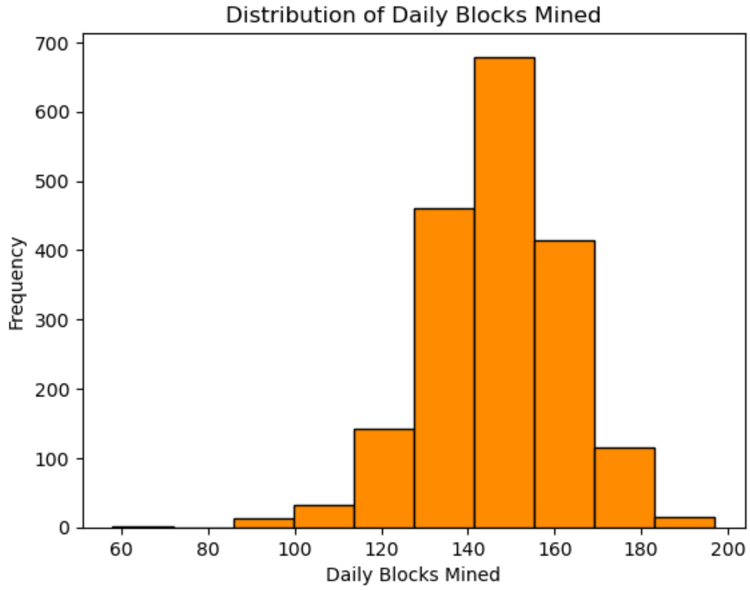
Source: own elaboration.

Figure 53: Boxplot Active Addresses.



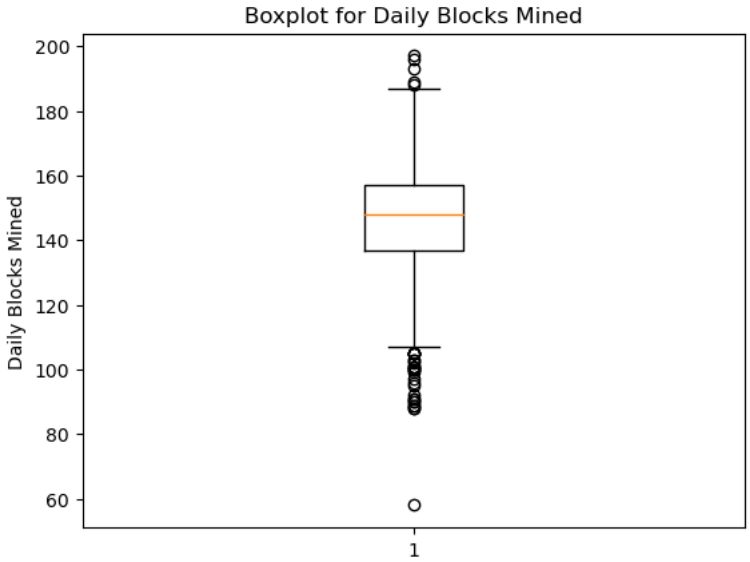
Source: own elaboration.

Figure 54: Distribution Daily Blocks Mined.



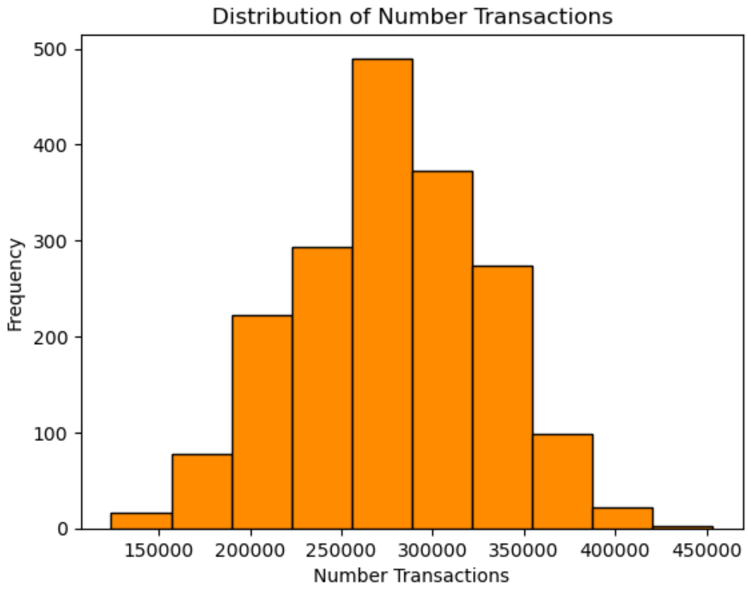
Source: own elaboration.

Figure 55: Boxplot Daily Blocks Mined.



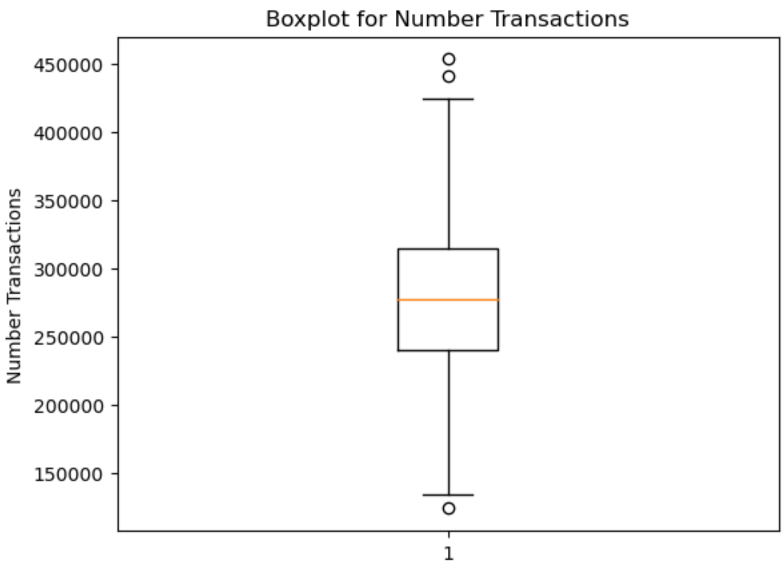
Source: own elaboration.

Figure 56: Distribution Number of Transactions.



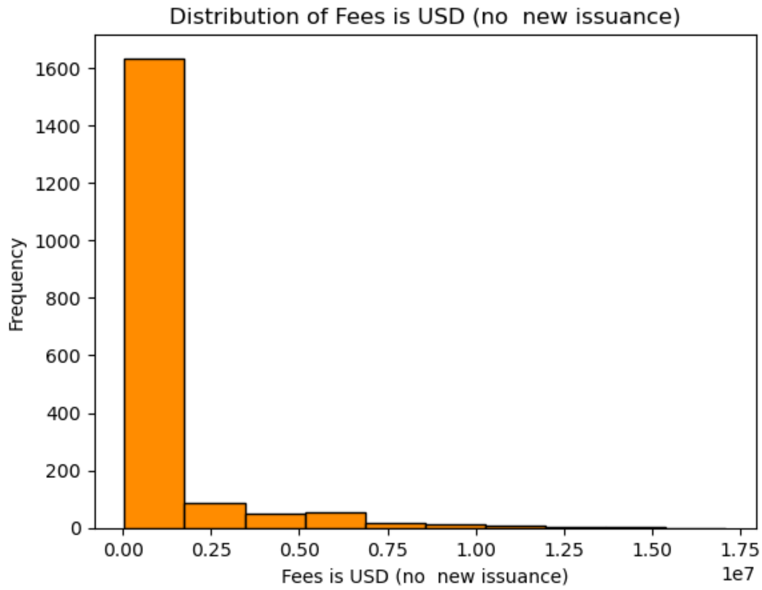
Source: own elaboration.

Figure 57: Boxplot Number of Transactions.



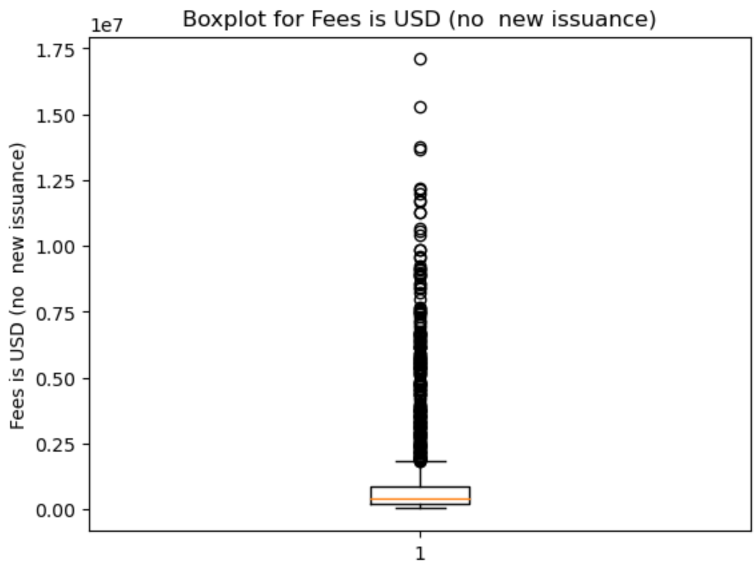
Source: own elaboration.

Figure 58: Distribution of Fees in USD.



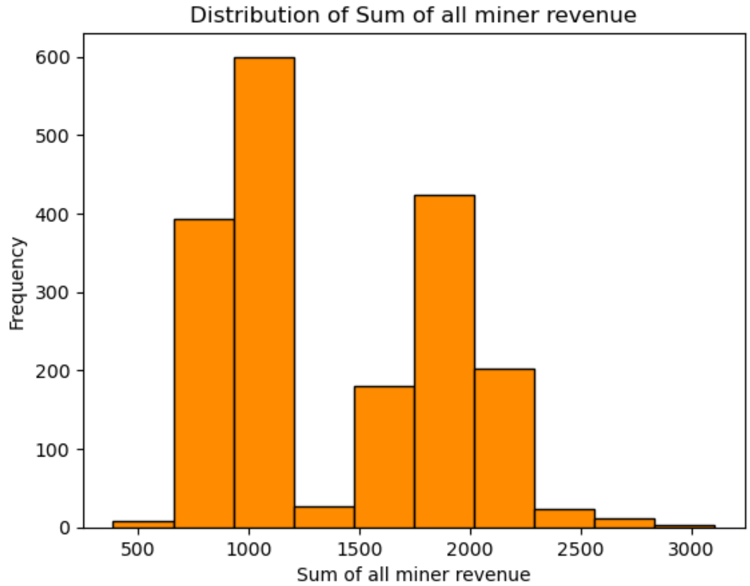
Source: own elaboration.

Figure 59: Boxplot Fees in USD.



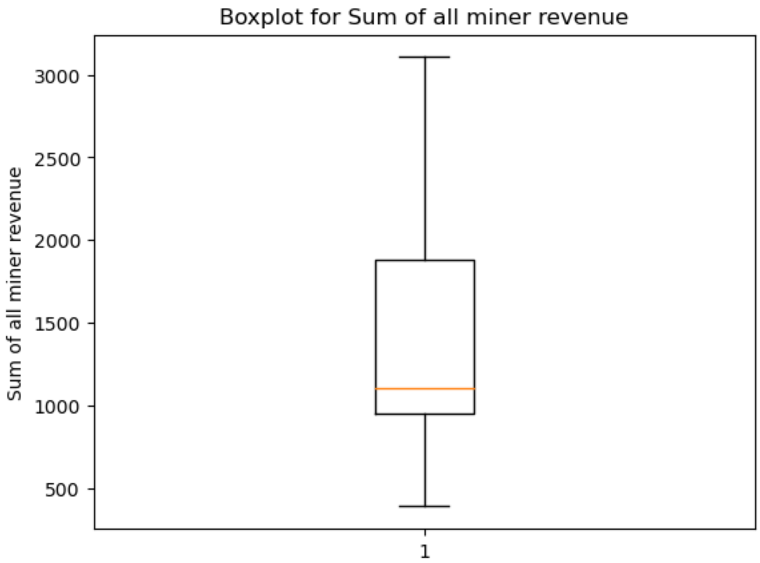
Source: own elaboration.

Figure 60: Distribution Miner Revenue.



Source: own elaboration.

Figure 61: Boxplot Miner Revenue.



Source: own elaboration.