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# Using crypto assets pricing methods to build technical oscillators for short-term bitcoin trading

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## Abstract

This paper examines the trading performances of several technical oscillators created using crypto assets pricing methods for short-term bitcoin trading. Seven pricing models proposed in the professional and academic literature were transformed into oscillators, and two thresholds were introduced to create buy and sell signals. The empirical back testing analysis showed that some of these methods proved to be profitable with good Sharpe ratios and limited max drawdowns. However, the trading performances of almost all methods significantly worsened after 2017, thus indirectly confirming an increasing financial literature that showed that the introduction of bitcoin futures in 2017 improved the efficiency of bitcoin markets.

*Keywords:* Bitcoin; Trading; Network to transactions ratio; Network value to realized value ratio; Network value to hashrate ratio; Active addresses metrics; INET model; Volt model; Technical oscillators.

*JEL classification:* C32, C51; C53; C58; G11, G12; G17; .

*Information, forthcoming*

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# 1 Introduction

In 2008, an anonymous developer named Satoshi Nakamoto published a white paper titled “Bitcoin: A Peer-to-Peer Electronic Cash System”, which proposed a new decentralized encrypted digital currency called Bitcoin (BTC) based on blockchain technology. In simple terms, the purpose of Bitcoin was to create a means for people to send money via the Internet as an alternative to traditional methods to transfer money. The blockchain is a public record-keeping system based on a linear chain that consists of blocks. The transaction information is recorded in the blocks and each block contains the cryptographic hash value and the timestamp of the previous block: given that each block has a hash pointer to the previous block, the data structure is similar to a chain. Once we know the hash value of the previous block, it can be compared with the hash value in the current block to determine whether or not its recorded transactions have changed, thus allowing a major defense against data tampering. A “miner” records the new transactions information and transfers them into a block, and then it has to solve a complex mathematical puzzle named Proof-of-work (PoW), which is a decentralized consensus mechanism that is employed to prevent anybody from gaming the system. The first miner that successfully solves this mathematical puzzle receives a reward and transaction fees in bitcoin for the confirmed block. At the start of 2009, the reward for each block was 50 BTC, and it is halved approximately every four years. As of 2022, the reward for one new block is 6.5 bitcoin. The total amount of new bitcoin to be issued is limited to 21 million, and this number will be reached around 2140.

Bitcoin and several other thousands crypto-assets are traded daily on a large number of crypto-exchanges <sup>1</sup>, with a total daily trading volume that -in some days- was higher than 100 billion dollars. In this regard, several methods have been proposed to estimate the fundamental value of Bitcoin, see Burniske and Tatar (2018), Fantazzini (2019) and Goutte et al. (2022) for an introduction at the textbook level. Besides, there is an increasing financial literature that proposed advanced non-linear models to predict Bitcoin returns using popular technical indicators representing market trend, momentum, volume, and sentiment, see e.g. Nakano et al. (2018), Huang et al. (2019), Gradojevic et al. (2021), Ortu et al. (2022) and references therein.

In this work, we followed in the footsteps of Woo (2018) and Kalichkin (2018), who were the first to use moving averages and z-scores to convert pricing models into technical oscillators, and we examined seven pricing models proposed in the professional and academic literature to create oscillators for bitcoin daily trading. We then computed two thresholds based on the quantiles of these oscillators to create buy and sell signals. Even though professional traders often use technical oscillators based on pricing models for crypto assets, such an approach is rarely discussed in the academic literature. This paper differs from

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<sup>1</sup>At the end of the first quarter of 2022, there were almost 300 exchanges listed on <https://coinmarketcap.com/rankings/exchanges>.

the aforementioned studies in that it is among the first to examine the profitability of a set of technical indicators based on pricing methods for crypto assets using more than ten years of Bitcoin data.

Our empirical back-testing analysis showed that some of these methods proved to be profitable with good Sharpe ratios and limited max drawdowns. . However, the trading performances of almost all methods significantly worsened after 2017, thus indirectly confirming an increasing financial literature that showed that the introduction of bitcoin futures in 2017 improved the efficiency of bitcoin markets.

We remark that crypto-assets can suffer from significant credit risk, which can take two forms: either the crypto asset "dies" (that is, a situation when its price drops significantly and it becomes illiquid), or the crypto exchange closes due to a bankruptcy, or a fraud, or a hacking attack. We did not consider such type of risk in our analysis, and we refer to Fantazzini and Zimin (2020), Fantazzini and Calabrese (2021), and Fantazzini (2022) for a detailed discussion.

The rest of this paper is organized as follows. Section 2 reviews the literature devoted to crypto assets valuation, while the technical oscillators proposed for trading bitcoin are discussed in Section 3. The empirical results are reported in Section 4, while two robustness checks are discussed in Section 5. Section 6 concludes.

## 2 Literature review

The last years have witnessed the emergence of several professional analyses and academic papers proposing a wide range of models to price crypto assets. We focus below on a specific selection of approaches that will be useful for our work, while we refer the interested reader to Goutte et al. (2022) -chapter 9- for a larger review.

### 2.1 Cost analysis

Berengueres (2018) performed a valuation of several crypto coins by using the net present value. He examined the hardware and software costs of crypto mining and highlighted a paradox: new miners are not profitable because old miners are simply able to update their old equipment in their farms (such as CPUs, GPUs or other infrastructure). Therefore, existing miners have a significant capital advantage over new mining groups. Thum (2018) analyzed the cost of a single miner, assuming that a new miner enter in a free market with an expected profit equal to zero. According to his model, the miner cost must equal the value of newly mined bitcoins.

Delgado-Mohatar et al. (2019) performed an analysis of the energy consumption of Bitcoin and argued that miners would not be profitable if the electricity price were to exceed \$0.14/kWh, showing that the marginal cost of mining Bitcoin was approximately \$1,952. Instead, Benetton et al. (2019)

focused mainly on environmental issues and attempted to construct a tax model for the crypto-coin mining industry. They noted that the total energy consumption of crypto coins is incredibly high: for example, in 2018, 0.3% to 0.5% of the energy consumed globally was used in mining, and crypto-coins accounted for 5% to 12% of carbon emission quotas. They noted that the growth of the market size of the Bitcoin network was not feasible due to its proof-of-work mining model. They suggested that the government could introduce a tax if the energy consumption due to mining were to create a pollution externality. They also introduced a “local decision model” including the average temperature, electricity prices, and the distance to the nearest power station, to help investors identify the optimal mining locations. They showed that, while crypto-coin mining can improve the local economy (more consumers and workers) and generate more tax revenues, it may also create energy shortages and increased use of fossil fuels.

## 2.2 Crypto-coin valuation

Romanchenko et al. (2018) analyzed different methods to assess the intrinsic value of crypto-coins using data from April 2014 until November 2018. They argued that crypto coins could be considered to be a currency-based commodity and that the intrinsic value of crypto coins can be divided into two parts: the commodity part that can be measured by the amount of labor involved, and the currency part that can be measured by the money velocity. However, they also admitted that the price of crypto coins can be influenced by the investors’ willingness to buy and sell.

Hargrave et al. (2019) suggested that there are three different categories of crypto coins: currency tokens, platform tokens, and asset-backed tokens. Currency tokens can be used for buying and selling goods and services in the real world and a typical example is bitcoin. Platform tokens can be used to run transactions and smart connections on the blockchain, and a typical example is Ethereum (ETH). Asset-backed tokens are tied to an underlying asset in the real world so that a coin unit can represent real estate ownership (for example). Hargrave et al. (2019) also noted that the value of crypto-coins depends on investor confidence, and ICOs should use a variety of methods for maintaining high market confidence. Moreover, they also suggested that the use of the Metcalfe’s law is appropriate for measuring the value of crypto coins (more about this topic below).

Jernej (2021) provides a review of the crypto-coin valuation models currently used in practice, which includes both professional approaches and academic approaches: the quantity theory of money, Chris Burniske’s INET model, Evans’ Volt model, ARK Invest model, and the Black-Scholes model. Finally, Kaal, Evans and Howe (2022) reviewed the asset valuation methods commonly used for stock pricing, and they found that these traditional valuation methods could hardly be applied to digital assets. Even

though there are commonalities, digital assets require a different analysis for pricing purposes. The methodologies currently proposed for digital asset valuation may vary significantly, and the lack of standards for the valuation of these assets can lead to uncertainty and confusion among investors and managers.

### 2.3 Social network analysis for cryptoassets modelling

Social network analysis (SNA) investigates social structures by using networks and graph theory. Networked structures are represented in terms of nodes, which can be individual actors, people, or items within the network, and the ties or links that connect them, which can be relationships or interactions. SNA can process a large amount of relational data and describe the general relational network structure. Moreover, the communication structure and the position of all individuals can be fully described by analyzing nodes, clusters and their relations, see Otte and Rousseau (2002) for an introductory survey, while Wasserman (1994), Yang et al. (2016) and Borgatti et al. (2018) for a discussion at the textbook level.

There is an increasing body of the financial literature that explores the key features of blockchains' network structures and how they affect the price dynamics of these crypto-assets. More specifically, a blockchain can be modeled directly through a social network because the social network nodes can represent the blockchain addresses, while its arcs can denote the transactions between the addresses corresponding to the involved nodes. Social Network Analysis based techniques can then be used to extract knowledge about the behavior of the blockchain actors involved, see Baumann et al. (2014), Kondor et al. (2014), Liang et al. (2018), Ferretti and D'Angelo (2019), Vallarano et al. (2020), Ao et al. (2022), and Bonifazi et al. (2022), just to name a few.

The network structures may differ significantly across blockchains: for example, Chang and Svetinovic (2016) found that the Bitcoin network has grown denser over time, with more nodes tending to be connected with each other, leading to a strong community while Namecoin has shown a decrease in density, resulting in an unclear community structure.

This literature has found significant effects of network features on economic variables such as price and volatilities. For example, Motamed and Bahrak (2019) found that the price of Bitcoin, Ethereum and Litecoin are positively correlated with the size of the graph and the number of nodes and edges, while Vallarano et al. (2020) showed that the price of Bitcoin is negatively correlated with the average outdegree<sup>2</sup>. Bove et al. (2019) used a Granger causality test and found that the past degree distributions (especially the outdegree of the Bitcoin trading network) can predict future price increases, while Li et al. (2019) built an ARIMA time-series model to forecast price anomalies using network features.

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<sup>2</sup> *Outdegree is the number of edges that are directed out of a node in the directed network graph.*

Finally, Bonifazi et al. (2021) presented a SNA-based approach to investigate user behavior during the speculative bubble involving Ethereum in the years 2017 and 2018 to extract knowledge patterns about this phenomenon, and to identify the speculators who were behind this Ethereum bubble.

## 2.4 Active addresses and Metcalfe's law

Alabi (2017) considered the number of unique addresses participating daily on the Bitcoin and Ethereum networks as a relative measure of the number of active users. He showed that the growth in the value of the network was significantly related to the number of unique addresses participating actively on the network. In this regard, the Metcalfe's Law of network value, which associates the value of the network with the square of its number of active users, was shown to model the networks quite well. In addition, he also proposed a new model that was derived and compared with Metcalfe's Law, which included a 30-day moving average filter. This model was found to be suitable for catching a bubble because if a higher price is not related to the growth of active addresses, it could potentially be a bubble.

Peterson (2018) compared the features of crypto coins with a now-defunct Italian telephone token called the *Gettone*, an ecosystem that married a telecommunications network with a currency, and which was active from 1927 to 2001. *Gettone* tokens were originally made of physical metal materials, but they were later replaced by magnetic calling cards in 1983. *Gettone* tokens could be used in daily life for telephone calls, as well as a form of currency to buy goods and services. One *gettone* was valued 50 lire up to 1980, 100 lire up to 1984, and 200 lire from 1984. It remained at this value until the introduction of the euro in 2001 in Italy, and it lost its monetary value since then. Peterson noted the similarities between the *Gettone* tokens and crypto coins. He then built a regression model based on Metcalfe's law and showed that bitcoin's medium- to long-term price followed this law quite closely with an  $R^2$  over 80%.

Garcia-Monleon et al. (2021) discussed the intrinsic values for different type of cryptocurrencies, including initial coin offerings (ICOs), single layer, and multiple layer coins. The purpose of an ICO is simply to raise funds for a specific coin project, whereas a single-layer coin works as a payment system to transfer currency, and its value is based on the active users in the network. A multiple-layer coin is Turing-complete and can be used to develop decentralized applications based on the needs of individuals or businesses. The operation of a new crypto-currency requires initial capital, which can be considered the initial intrinsic value of the crypto coins. If crypto-coins are accepted by the market and they can be used in daily life, the payments for goods and services can be used to measure the intrinsic value of crypto-coins. Garcia-Monleon et al. (2021) suggested the use of Metcalfe's law for measuring the intrinsic value of crypto coins. They argued that if popular online payment methods such as Visa and

PayPal could be valued in this way, then Metcalfe’s law could also be applied to single-layer and multiple layers coin, given that PayPal, Visa and crypto-coin networks all possess similar characteristics.

Stylianou, Spiegelberg, Herlihy and Carter (2021) analyzed the impact of network effects (user-based growth) and crypto-coin trends. They considered data for six crypto coins up to January 2020 and assumed that the growth of the network value was proportional to the number of users on the network. They concluded that network effects affected crypto-coin prices, but these effects did not provide crypto-coins with any competitive advantage.

Sabalionis, Wang and Park (2021) analyzed how the amount of Google search interest, the number of tweets, and the number of active addresses on the blockchain impacted the prices of Bitcoin and Ethereum over time. They used vector autoregressive (VAR) models with multivariate generalized autoregressive conditional heteroskedasticity (GARCH), and data between July 2017 and February 2018. They found that the number of active addresses was the most significant variable influencing the price movements of these crypto-assets, whereas Google searches and the number of tweets had weaker effects. There is also an increasing literature that investigated the determinants of the returns and volatility of cryptocurrencies using different measures of social media sentiment, the Economic Policy Uncertainty index, gold prices and herding behaviors, see Papadamou et al. (2021a,b), Kyriazis et al. (2022) and references therein.

## 2.5 Ratios of crypto-coins

The Network Value to Transactions (NVT) ratio first made its appearance in February 2017 in a tweet, but was discussed in more details in an article published on Forbes later in 2017 by Willy Woo (2017). Kalichkin (2018) later improved the NVT-ratio by proposing the NVT Signal (NVT Signal), which is the network value divided by the 90-day moving average of the daily transaction value and provides more insight for forecasting price tops. Partly inspired by the NVT Signal ratio, Mahmudov and Puell (2018) proposed the Market-Value-to-Realized-Value (MVRV), which is the market value divided by the realized value. The market value is the current last known price multiplied by the current circulating supply, while the realized value considers the lost and unmoved bitcoins and it is calculated by summing the products of price per bitcoin and the so called “Unspent Transaction Output” (UTXO). By dividing the market value by the realized value, an indication of Bitcoin’s real value emerges: Mahmudov and Puell (2018) found that, historically, a MVRV-ratio above 3.7 denotes overvaluation, whereas a MVRV-ratio below one indicates undervaluation.

Liu (2019) and Liu and Zhang (2022) found that fundamental market ratios have relatively little impact on short-term bitcoin returns. They employed machine learning methods and deep learning methods to create trading strategies: they found that the Price-to-Earning (PE) is not a good crypto-



coin indicator, and they highlighted the limitations of the network value-to-transaction (NVT) ratio, which ignores the store-of-value function. Given this evidence, they proposed a new ratio called the price-to-utility (PU) ratio and built a trading strategy that gives a buy signal when the PU ratio goes below the 10% quantile and a sell signal when the PU ratio exceeds the 90% quantile. They argued that this strategy outperforms traditional moving average crossover strategies, and that the token utility is a leading indicator for the token price. However, the main limitation of this kind of ratios is that they cannot be used to compare the valuations of coins with different features (such as Bitcoin and Ethereum, for example), as recently highlighted by Gotte et al. (2022).

### 3 Materials and Methods

The previous literature review found no detailed analysis of the profitability of the proposed pricing methods for short-term trading, and all these approaches focused on medium and long-term evaluation. Among all the methods reviewed, the approaches using the ratios of crypto-coins and the metrics based on active addresses appeared to be the most apt for short-term trading. Therefore, given that the goal of our work was to examine the trading performances of technical oscillators created using crypto assets pricing methods, we selected seven pricing models proposed in the previously reviewed professional and academic literature.

Before presenting the results of the empirical analysis, we briefly review these crypto-assets pricing methods, and we discuss in detail how to use them to create technical oscillators and buy and sell trading signals.

#### 3.1 Network-to-transactions ratio (NVT)

The network-to-transactions (NVT) ratio was originally proposed by Woo (2017), and it is reported below,

$$NVT = \frac{\text{Network Value}}{\text{Transaction Value}} = \frac{\text{Market Capitalization}}{\text{Transaction Value}} \quad (1)$$

where the network value is usually measured with the crypto-asset market capitalization in US dollars (USD), while the transaction value is the total transaction volume in USD that took place in a specific period (daily, monthly, or yearly).

The proposed model was originally developed from the price-to-earnings (PE) ratio, which is a traditional method used in financial analysis. If the NVT ratio is too high, so the network value is much greater than the total transferred on-chain value for a specific period, it means that the market is overvalued and it has high expectations for this crypto asset. If the NVT ratio is too low, the network value

is much smaller than the total transferred on-chain value, which means that the market is undervalued and it has low future expectations.

If we use the definition of market capitalization and transaction value,

$$\begin{aligned} \text{Market Capitalization} &= \text{Supply}_{\text{Token}} \cdot \text{Price}_{\text{Token}} \\ \text{Transaction Value} &= \text{Transaction Volume}_{\text{Token}} \cdot \text{Price}_{\text{Token}} \end{aligned}$$

And we substitute them into the NVT ratio, we obtain

$$NVT = \frac{\text{Supply}_{\text{Token}} * \text{Price}_{\text{Token}}}{\text{Transaction Volume}_{\text{Token}} * \text{Price}_{\text{Token}}} = \frac{\text{Supply}_{\text{Token}}}{\text{Transaction Volume}_{\text{Token}}}$$

Given that the token transaction volume over the token supply is the money velocity, the NVT is the reciprocal of the money velocity:

$$NVT = \frac{1}{\text{Velocity}}$$

The NVT ratio is very volatile, so using this ratio as an indicator is rather difficult. To solve this problem, Kalichkin (2018) modified the ratio (1) as follows,

$$NVTS = \frac{\text{Network Value}}{MA_{\text{Transaction Value}}} \quad (2)$$

where he used the moving average (MA) of the transaction value to smooth the NVT ratio. Woo (2018) modified the Kalichkin's NVTS model (2) to the so-called "adjusted-NVTS ratio", which is an oscillator indicator able to generate buy and sell signals. However, he did not provide any formula, and he simply stated that "the adjusted-NVTS displays how many standard deviations NVTS is above or below its historical norm. The historical norm is the 2-year moving average of NVTS, similarly, the standard deviation calculation uses a 2-year sampling" (Woo, 2018). Therefore, it appears that he used the well-known z-score to standardize the NVTS ratio,

$$NVTSZ(a, b) = \frac{NVTS - \mu}{\sigma} \quad (3)$$

where  $\mu$  is the mean value of the NVTS ratio computed over a specific period of time  $b$  (with  $b=2$  years),  $\sigma$  is the standard deviation over the same period  $b$ , while  $a$  is the time sample used to compute the moving average of the network transaction value in eq. (2).

### 3.2 Network value to realized value ratio (NVRV)

The network value to realized value (NVRV) ratio was first introduced by Mahmudov and Puell (2018), and it is computed as follows,

$$NVRV = \frac{Network\ Value}{Realized\ Value} \quad (4)$$

where the network value and realized value are measured in USD, and they are given by,

$$\begin{aligned} Network\ Value &= Last\ trade\ coin\ price \cdot All\ coins\ in\ circulation \\ Realized\ Value &= \sum_i Last\ trade\ price\ of\ each\ coin_i \end{aligned}$$

Unlike traditional stock markets, each crypto-coin transaction and the last trade price for each coin can be tracked, and their summation gives the realized value of the coin market capitalization, see Coinmetrics (2018) for more details. When the NVRV ratio is greater than one, the market is overvalued and in a stage of euphoria. Conversely, if the NVRV ratio is lower than one, the market is undervalued and in a stage of capitulation-despondency.

A variant of this ratio using the z-score was originally introduced by Wonder (2018):

$$NVRVZ(a, b) = \frac{NVRV - \mu}{\sigma} \quad (5)$$

where  $\mu$  is the mean value of the NVRV ratio computed over a specific period of time  $b$ ,  $\sigma$  is the standard deviation over the same period  $b$ , while  $a$  is the time sample used to compute the moving average of the NVRV in equation (4).

### 3.3 Network value to hashrate ratio (NVHR)

The network value to hashrate ratio measures a crypto asset network value in dollars per unit of hashrate, see 21Shares (2020) for more details. Its formula is reported below:

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

The NVHR ratio measures the expectations of investors for a specific coin: when the NVHR is high, investors have positive expectations and are willing to invest more, but if it is low, they have negative expectations and are willing to invest less or exit the market. Another possible interpretation is that a higher value of the NVHR ratio suggests that an investor is willing to pay more to receive the economic security granted by the current crypto asset hashrate, whereas a lower value of the NVHR ratio suggests that an investor is willing to pay less for the economic security granted by the current asset's hashrate.

Given that the NVHR ratio can fluctuate wildly, it is smoothed using a moving average of the daily hashrate value,

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

Similar to previous ratios, we transform it into an oscillator using the z-score for trading purposes,

$$NVHRSZ(a, b) = \frac{NVHRS - \mu}{\sigma} \quad (6)$$

where  $\mu$  is the mean value of the NVHR ratio computed over a specific period of time  $b$ ,  $\sigma$  is the standard deviation over the same period  $b$ , while  $a$  is the time sample used to compute the moving average of the hashrate.

To smooth the jitter at the peaks and troughs of the previous ratio (6), a variant using the exponential moving average (EMA) can be employed:

$$NVHRSZ(a, b, c) = EMA \left( \frac{NVHRS - \mu}{\sigma} \right) \quad (7)$$

where  $c$  is the number of days used to compute the exponential moving average.

### 3.4 Active addresses metrics.

Active addresses metrics are based on the addresses of crypto coins that are recognized as unique individual accounts (21Shares, 2020). Active addresses include all account addresses, independently of the fact that they are sending, receiving, or both. Another factor is the network value, which is measured by the coin market capitalization. These metrics are quite similar to the number of "daily active users" and to their daily activities, and they can be presented in two forms, using Metcalfe's law or Odlyzko's law.

Metcalfe's law was originally proposed to model the network effect of fax machines, telephones, networks, and other communication technology. It was formulated in the current form by George Gilder in 1993 who attributed it to Robert Metcalfe in regard to his work with Ethernet in the 1980s, see Shapiro et al. (1998) and Metcalfe (2013) for more details.

According to Metcalfe's law, the value of a telecommunications network is proportional to the square of the number of connected users of the system:

$$ML\ Value = A \cdot n^2$$

where  $A$  is a coefficient and  $n$  is the number of connected system users. Odlyzko et al. (2006) improved

this model and showed that the incremental value of adding one person to a network of  $n$  people is approximately the  $n$ -th harmonic number, so the total value of the network is given by,

$$OL\ Value = n \log n$$

### 3.4.1 Network value to Metcalfe's law ratio

If we assume that the Metcalfe's law for crypto-coins can be approximated as follows,

$$ML \approx (Active\ Addresses)^2$$

then the network value to Metcalfe's law (NVML) ratio is given by,

$$NVML = \frac{Network\ Value}{ML}$$

A moving average can be used to smooth the previous ratio,

$$NVMLS = \frac{Network\ Value}{MA_{ML}}$$

while the traditional z-score can be employed to standardize it and create an oscillator for trading purposes:

$$NVMLSZ(a, b) = \frac{NVMLS - \mu}{\sigma} \quad (8)$$

where  $\mu$  is the mean value of the NVML ratio computed over a specific period of time  $b$ ,  $\sigma$  is the standard deviation over the same period  $b$ , while  $a$  is the time sample used to compute the moving average. Again, to smooth the jitter at the peaks and troughs of the previous ratio (8), a variant using the exponential moving average (EMA) can be employed:

$$NVMLSZ(a, b, c) = EMA \left( \frac{NVMLS - \mu}{\sigma} \right) \quad (9)$$

where  $c$  is the number of days used to compute the exponential moving average.

### 3.4.2 Network value to Odlyzko's law ratio

If we assume that the market value of a crypto asset depends on Odlyzko's law as follows,

$$OL \approx Active\ Addresses \cdot \log(Active\ Addresses)$$

then the network value to Odlyzko's law (NVOL) ratio is given by,

$$NVOL = \frac{\text{Network Value}}{OL}$$

A moving average can be used to smooth the previous ratio,

$$NVOLS = \frac{\text{Network Value}}{MA_{OL}}$$

while the traditional z-score can be employed to standardize it and create an oscillator for trading purposes:

$$NVOLSZ(a, b) = \frac{NVOLS - \mu}{\sigma} \quad (10)$$

where  $\mu$  is the mean value of the NVML ratio computed over a specific period of time  $b$ ,  $\sigma$  is the standard deviation over the same period  $b$ , while  $a$  is the time sample used to compute the moving average. Again, to smooth the jitter at the peaks and troughs of the previous ratio (10), a variant using the exponential moving average (EMA) can be employed:

$$NVOLSZ(a, b, c) = EMA \left( \frac{NVOLS - \mu}{\sigma} \right) \quad (11)$$

where  $c$  is the number of days used to compute the exponential moving average.

### 3.5 A variant of the INET model for short-term trading.

The INET model was developed by Burniske (2017) to value the (fictitious) INET Token program. His starting point is the quantity theory of money, which argues that the price level of goods and services is proportional to the amount of money in circulation, and it builds upon the following equation,

$$M_0V = PQ = Y$$

where  $M_0$  is the monetary base,  $V$  is the money velocity,  $P$  is the price of the digital resource that is being provisioned,  $Q$  is the quantity of this digital resource, while  $Y$  is the gross domestic product (GDP) of the crypto-economy based on this digital asset.

If we use the expenditure method to measure the GDP of crypto-assets, we have that,

$$Y = \text{Transfer Value for consumers} = P_{\S} \cdot M_C$$

where  $M_C$  is the total transferred coins on-chain for consumption, while  $P_{\S}$  is the price of the crypto

asset measured in US dollars. We already know from section 3.1 that the NVT ratio is the reciprocal of the money velocity  $V$ , so that  $V$  can be obtained as

$$V = \frac{1}{NVT}$$

If we combine the previous equations together, we can get the so-called monetary-based crypto-coin value in US dollars  $M_{0\$}$ ,

$$M_{0\$}V = \frac{M_{0\$}}{NVT} = P_{\$} \cdot M_C, \quad \Rightarrow$$

$$M_{0\$} = P_{\$} \cdot M_C \cdot NVT$$

If we compare  $M_{0\$}$  and the total supply of the crypto-asset  $M_0$ , we get:

$$P'_{\$} = \frac{M_{0\$}}{M_0} = \frac{P_{\$} \cdot M_C \cdot NVT_t}{M_0} = P_{\$} \cdot \left( \frac{M_C}{M_0} \cdot NVT_t \right)$$

Since we already know that the NVT is the ratio of the total coin supply  $M_0$  over the transaction volume  $M_T$ , we can rewrite the previous equation as follows:

$$P'_{\$} = \left( \frac{M_C}{M_0} \cdot \frac{M_0}{M_T} \right) \cdot P_{\$} = \left( \frac{M_C}{M_T} \right) \cdot P_{\$} \quad \Rightarrow$$

$$e = \frac{P'_{\$}}{P_{\$}} = \left( \frac{M_C}{M_T} \right)$$

where  $e$  can be considered a sort of reciprocal ratio of M2/GDP for the crypto-economy based on this crypto asset.

Even though every single transaction is recorded on the blockchain, determining the purpose of a specific transaction can be difficult due to the anonymity of the blockchain network. Instead, the speculation volume is easy to identify for bitcoin and most crypto assets: these transactions are performed via crypto exchanges and can be analyzed in a straightforward manner. Therefore, if the speculation volume substitutes the consumption volume, we get the following ratio<sup>3</sup>:

$$InetSpe = \left( \frac{M_e}{M_T} \right) \tag{12}$$

where  $M_e$  is the speculation volume. If this indicator is high, the proportion of speculative transactions has increased, whereas if it is low, the proportion of speculative transactions has decreased. This ratio is often used for trading purposes. We remark that in the original Chris Burniske's model for annual data,

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<sup>3</sup> The name of the ratio *InetSpe* was chosen to show that this ratio is a variant of the *INET* model for short-term trading, that is for speculation purposes.

there is an additional part used for computing the present value of a coin. However, we focus here on daily data for short-term trading, so this part is not considered.

We can transform the ratio (12) into an oscillator using the usual standardization procedure:

$$InetSpeZ(a, b) = \frac{InetSpe - \mu}{\sigma} \quad (13)$$

where  $\mu$  is the mean value of the InetSpe ratio computed over a specific period of time  $b$ ,  $\sigma$  is the standard deviation over the same period  $b$ , while  $a$  is the time sample used to compute the moving average.

### 3.6 Volt valuation model.

Alex Evans (2018) proposed a framework for modelling the money velocity using the Baumol-Tobin model, which is related to the transaction demand for money, transaction costs, and the risk-free rate of investment interest<sup>4</sup>. He assumes that a player in the economy will spend all his/her annual income during a specific year and that the player has two choices: either hold his money in cash, or save his income in an interest bearing bank and then make partial withdrawals when necessary. The last choice makes the player earn some money, but it also implies a lot of transaction costs. To find the optimal choice, the player must find the optimal number  $N$  of withdrawals needed to maximize his/her earnings. Evans found that the optimal  $N$  is given by,

$$N_{Volt} = \sqrt{\frac{R \cdot Y}{2C}}$$

where  $R$  is the nominal free-risk interest rate,  $Y$  is the average payment per user per year and  $C$  is the transaction cost, while the money demand function is estimated as,

$$M_{Volt} = \sqrt{\frac{Y \cdot C}{2R}}$$

A ratio for trading purposes can be computed by comparing the network value to the Volt money demand for a specific coin,

$$NVVolt = \frac{Network\ Value}{M_{Volt}} \quad (14)$$

while an oscillator can be built using (14) as follows:

$$NVVoltZ(a, b) = \frac{NVVolt - \mu}{\sigma}$$

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<sup>4</sup> *VOLT is the name of Evans' fictitious token.*



where  $\mu$  is the mean value of the *NVVolt* ratio computed over a specific period of time  $b$ ,  $\sigma$  is the standard deviation over the same period  $b$ , while  $a$  is the time sample used to compute the moving average. To smooth the jitter at the peaks and troughs, the exponential moving average can be used again in the usual way:

$$NVVoltZ(a, b, c) = EMA\left(\frac{NVVolt - \mu}{\sigma}\right) \quad (15)$$

where  $c$  is the number of days used to compute the exponential moving average.

### 3.7 Trading strategy.

Once all models were converted into oscillators, we had to compute the two thresholds used for trading purposes, that is the short threshold and the long threshold. Both thresholds were computed using the oscillators' quantiles: following Romano et al. (2019), Liu (2019) and Liu and Zhang (2022), we used the 5% quantile as the signal to enter a long position and the 95% quantile as the signal to sell and close our position <sup>5</sup>. More specifically, when the oscillator was less than the long threshold, the crypto-coin was considered to be in the oversold zone, but when the oscillator started crossing above the long threshold, the crypto-coin was considered to be leaving the oversold zone, and the model created a long signal. Similarly, when the oscillator was greater than the short threshold, the crypto-coin was considered to be in the overbought zone, but when the indicator crossed below the short threshold, the crypto-coin was believed to be leaving the overbought zone and falling back, so the model created a short signal.

We remark that short-selling always involves a liquidation risk, particularly with high-risk financial assets such as crypto-coins. Therefore, we only considered long positions in this work, whereas short-selling was discarded. For testing the profitability performance of an oscillator, we used the most straightforward strategy: when the indicator gave a buy signal, one bitcoin was purchased, while it was later sold when a sell signal was triggered. Theoretically, a trading strategy should include take-profits and stop-losses, but such strategies strongly vary among individuals: some people may prefer to exit when the floating loss is greater than 5%, whereas others prefer 10%. Aggressive investors may place stops at 40% or 50% of the initial position. Moreover, some traders may set up more complex stop-loss strategies involving options to hedge losses. In this work, we did not consider stop-loss (or take-profit) strategies, and we focused only on the profitability of the buy and sell signals that were generated by the competing models. We leave this issue as a topic for future research. For simplicity, we considered an account with initial equity equal to 500 thousand USD.

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<sup>5</sup>The two thresholds could have been optimized, but this computation would have added a layer of complexity (and potentially also over-fitting) to our work. This is why we did not consider such an extension here, and we leave it as an avenue for further research.

### 3.7.1 Parameters of the moving averages and z-scores

These parameters can be chosen arbitrarily and there is no definitive method. For example, in the case of the well-known MACD oscillator, some investors employ the 200-day and 50-day moving averages as signals, while others prefer the 100-day and 50-day moving averages as signals. In the case of crypto-assets, Kalichkin (2018) believed that a moving average of 90 days *”is a better proxy for long-term fundamental value”*. Quarterly reports are also known to have an impact on the stock market and they are generally released a few weeks after the conclusion of a quarter. The effect of quarterly reports on the crypto-coins market is currently unknown: for example, it is known that Tesla CEO Elon Musk is one of the main promoters of crypto-coins and his tweets can impact the crypto-coin market (see Huynh (2022) and references therein), but it is unknown whether Tesla’s quarterly reports can affect crypto-coins. Microsoft, Tesla, PayPal, Coinbase, and other large companies that are supportive of crypto coins are generally listed on the US stock market: considering the quarterly reports of these companies, a sample of 120 days may be a good choice for computing the z-scores. Given this evidence, we employed 90 days to compute the moving averages, while a sample of 120 days to compute the z-scores of our trading models. As for the EMAs, whose purpose was to reduce the jitter of the oscillators at the peak, we employed samples of 7 or 14 days, depending on the specific model used. We justify this choice because larger samples may make the oscillators too flat, and no more useful for providing trading signals.

### 3.7.2 Trading strategy evaluation metrics

To backtest the trading performances of the models discussed in this work, we employed several metrics implemented in the `blotter` R package. The `blotter` R package provides transaction infrastructure for defining transactions, portfolios and accounts for trading systems and simulation. Moreover, it provides portfolio support for multi-asset class and multi-currency portfolios. We refer to the help manuals available at <https://github.com/braverock/blotter> for more details. We remark that the `blotter` package computes a much larger set of performance metrics, which are not reported here for sake of space and interest. The full results are available from the authors upon request. These metrics are briefly discussed below in Table 1:

<i>Metrics' acronym</i>	<i>Meaning</i>
<b>Net.Trading.PL</b>	Net trading profit and loss
<b>Ann.Sharpe</b>	Annualised Sharpe ratio.
<b>Max.Drawdown</b>	Maximum drawdown. It is the maximum accumulated loss for a portfolio position from its peak to its trough, before a new peak is attained. It is an indicator of downside risk over a specified period.
<b>Profit.To.Max.Draw</b>	Profit to max drawdown. It is a risk-adjusted return measure used as an alternative to the Sharpe ratio. This indicator represents profit expectations per unit of drawdowns.
<b>Max.Equity</b>	Maximum floating profit of the entire strategy during the backtest period
<b>Min.EquityNum.Txns</b>	Maximum floating loss of the entire strategy during the backtest period Number of transactions

Table 1: Evaluation metrics' acronyms and meaning.

## 4 Results

### 4.1 Data

We used daily bitcoin data (BTC) from August 17, 2011 to March 30, 2022 obtained from Glassnode, and whose download links are reported in the Appendix A. A brief description of the variables used in the empirical analysis is reported in Table 2, while their plots are reported in Figures 1-7.

<i>Factor</i>	<i>Unit</i>	<i>Description</i>
<b>Price</b>	USD	Daily close price
<b>Network value</b>	USD	Market capitalization
<b>Transaction value</b>	USD	The total estimated value of daily transactions on the block chain
<b>Realized value</b>	USD	Market capitalization measured by the last trade price of each coin
<b>Active addresses</b>	Number	The number of addresses that were sent or received
<b>Network hashrate</b>	Number	The hashrate of the total Bitcoin network
<b>Transaction in exchanges</b>	Number	The total estimated value of daily transactions within exchanges
<b>Risk-free rate</b>	Number	United States 10-year Treasury Rate

Table 2: Description of the variables used in the empirical analysis.

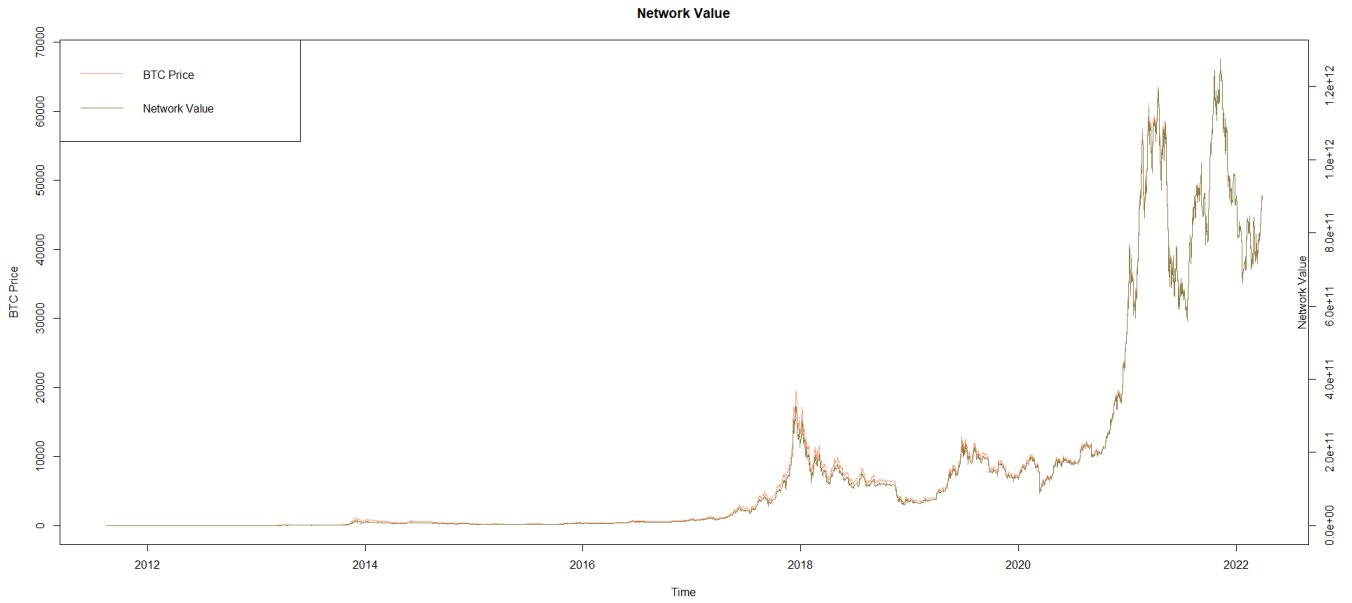


Figure 1: Bitcoin price and network value.

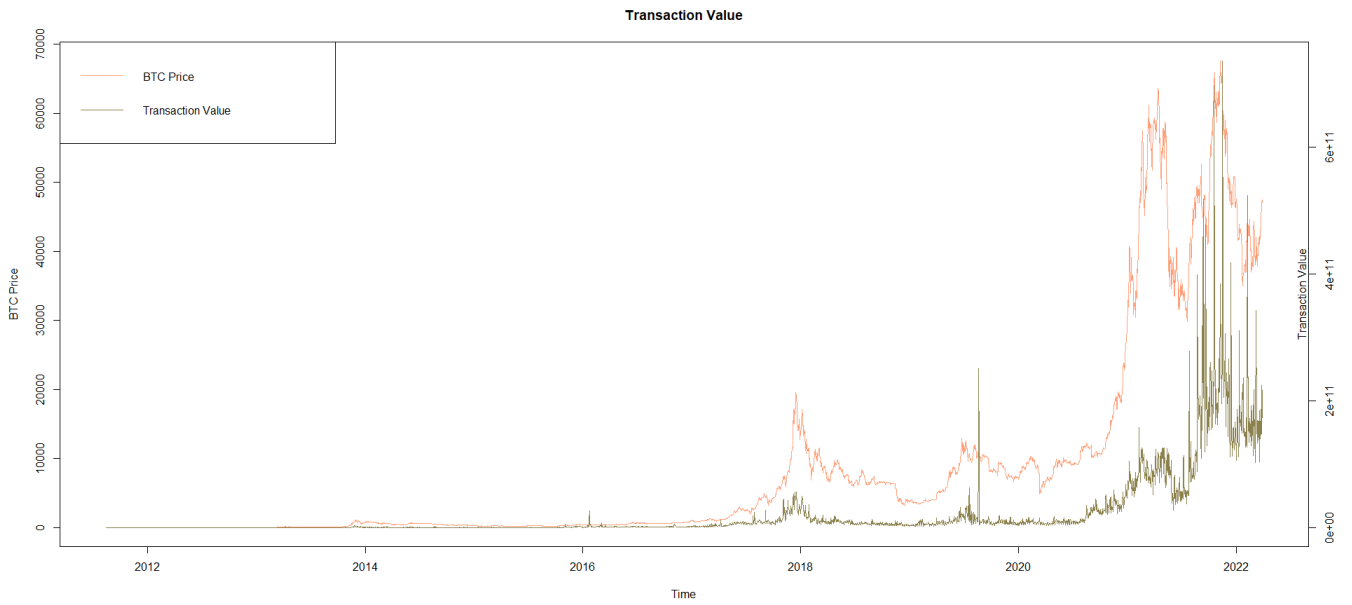


Figure 2: Bitcoin price and daily transaction value.

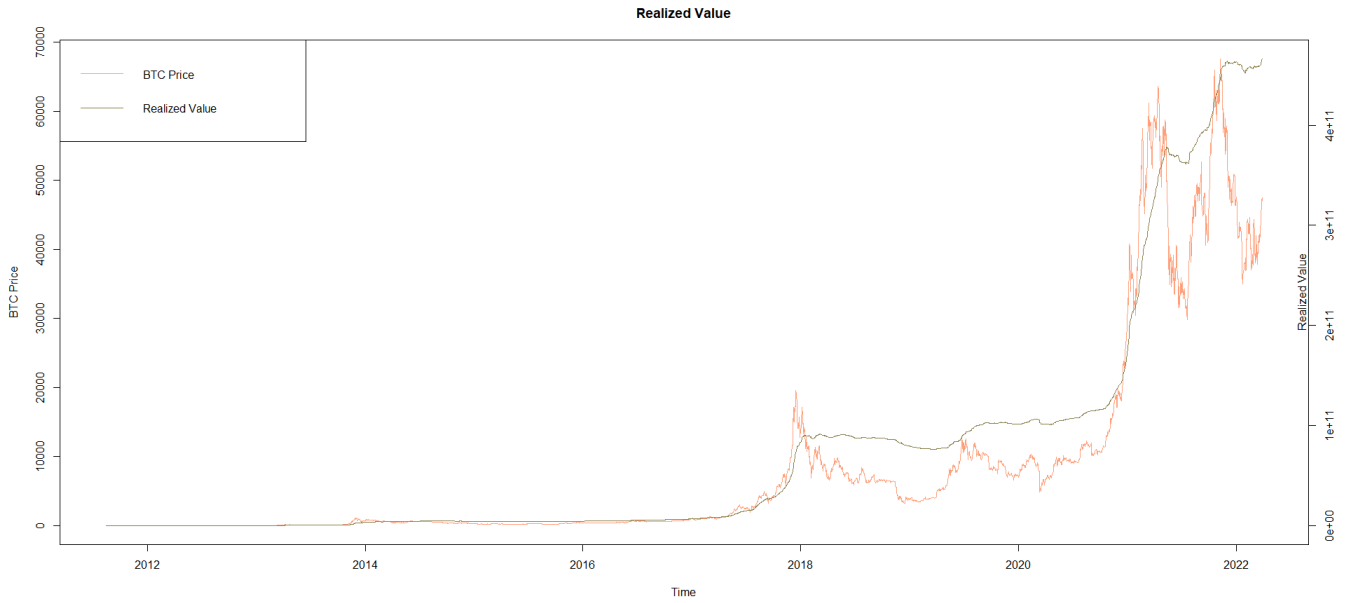


Figure 3: Bitcoin price and realized value.

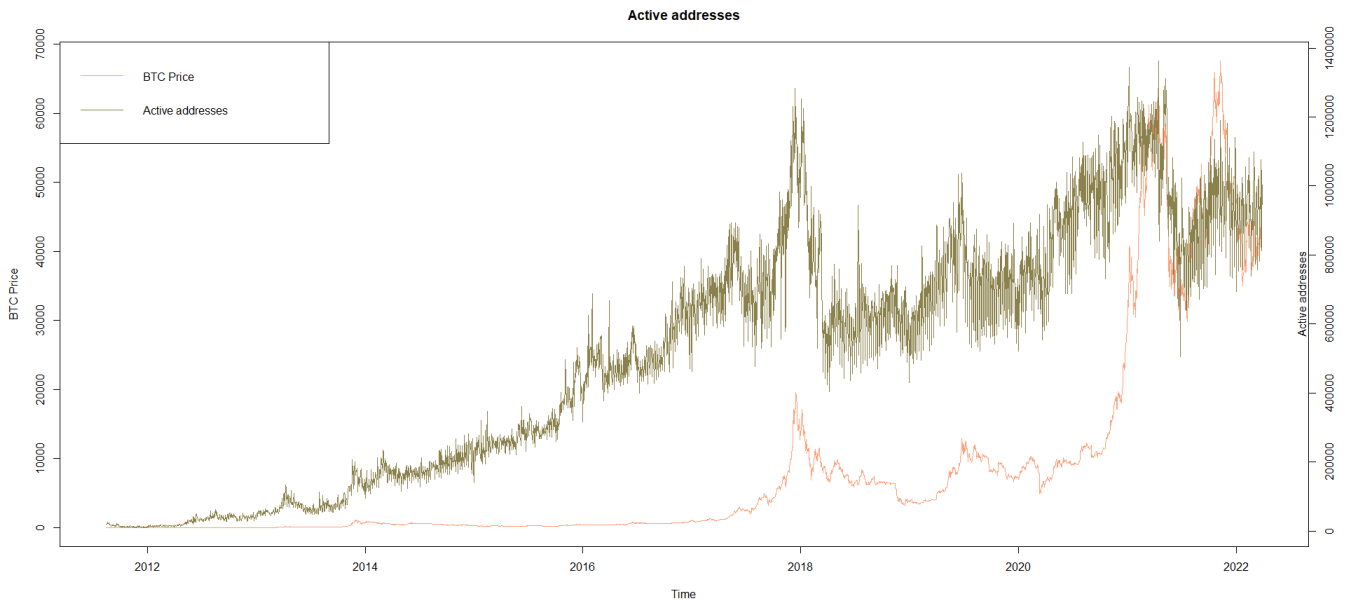


Figure 4: Bitcoin price and active addresses.

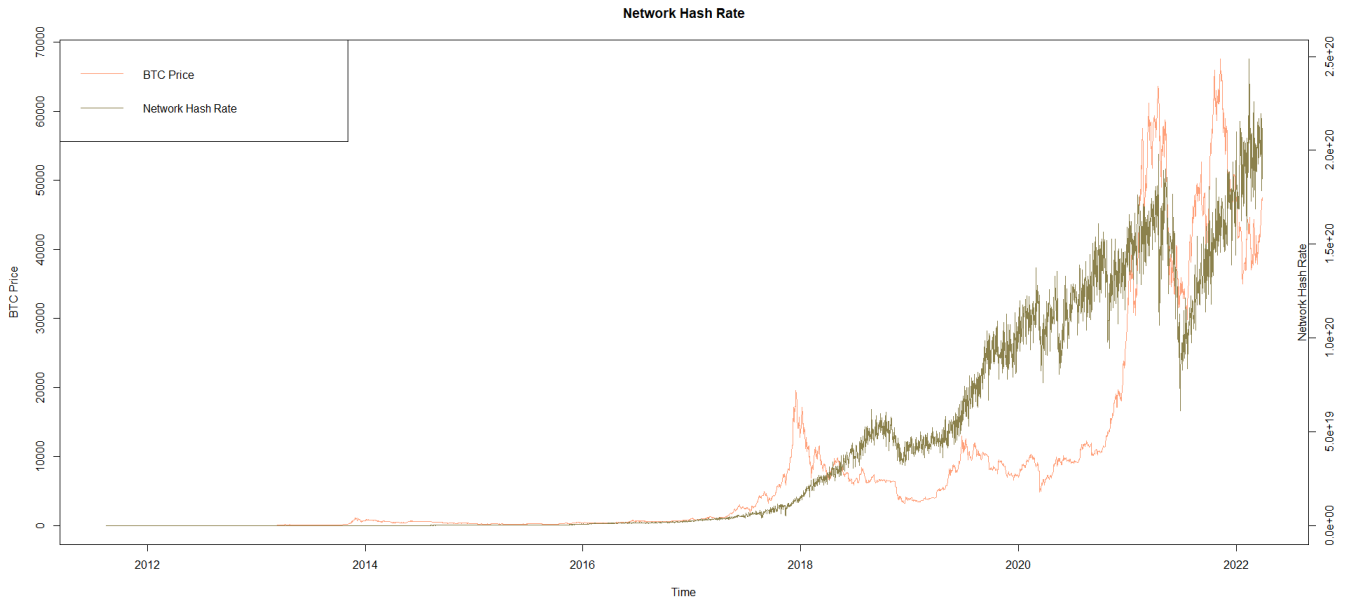


Figure 5: Bitcoin price and network hashrate.

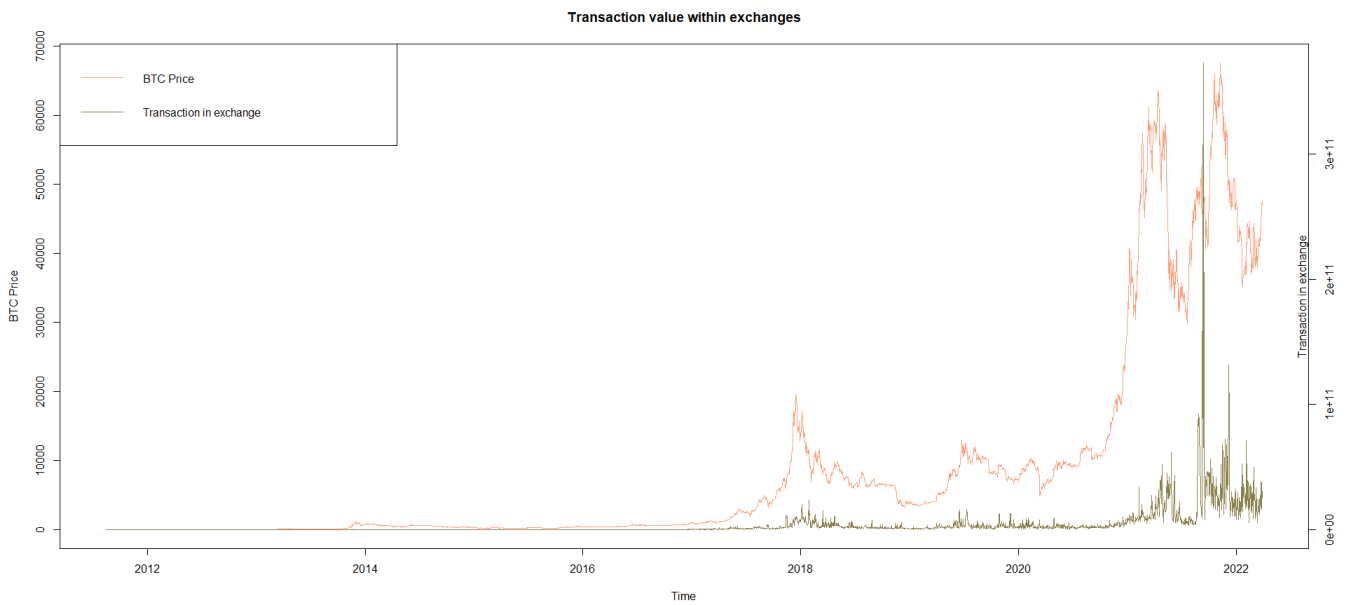


Figure 6: Bitcoin price and daily transactions value within exchanges.

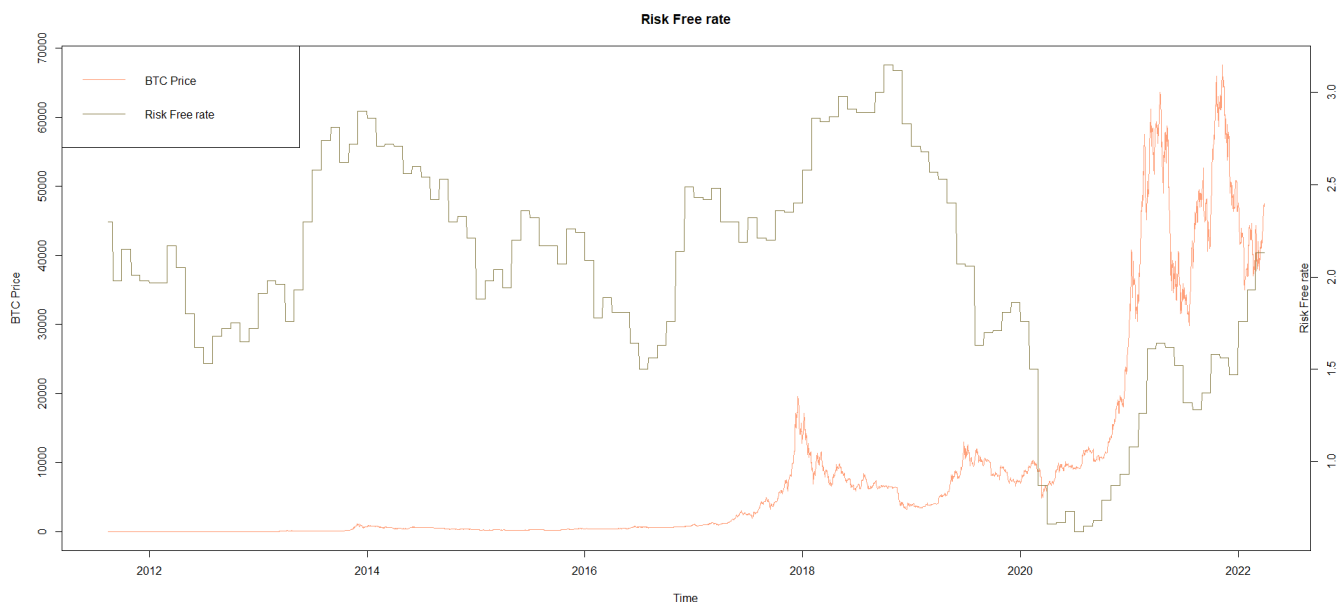


Figure 7: Bitcoin price and risk-free rate.

The descriptive statistics, the Jarque-Bera normality test statistics and p-values, and the KPSS unit root test statistics for the BTC price, BTC log-returns and for the seven technical oscillators are reported in Table 3, while the Figures A1-A7 in the Appendix B reports the technical oscillators computed for each trading strategy.

	<i>BTC (price)</i>	<i>BTC (log-ret.)</i>	<i>NVTS_Z</i>	<i>NVRV_Z</i>	<i>NVHRS_Z</i>	<i>NVMLS_Z</i>	<i>NVOLS_Z</i>	<i>INETSPE_Z</i>	<i>VOLT</i>
Mean	8879.61	0.00	0.03	0.23	-0.08	0.11	0.36	0.02	0.51
Median	1183.81	0.00	-0.05	0.05	-0.62	-0.12	0.32	-0.26	0.52
Maximum	67589.01	0.34	4.83	3.74	3.95	4.12	4.25	3.47	4.42
Minimum	4.55	-0.68	-5.41	-3.31	-3.05	-3.49	-3.48	-2.66	-3.05
Skewness	2.16	-1.48	0.18	0.27	0.70	0.37	0.21	0.87	0.12
Kurtosis	6.60	29.00	2.49	2.38	2.43	2.32	2.28	3.53	1.99
Jarque-Bera	4831	104600	58	102	353	153	106	506	163
P-value JB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
KPSS test	4.36*	0.18	0.11	0.16	0.22	0.31	0.15	0.07	0.38

\* The null hypothesis of stationarity is rejected at the 5% probability level.

Table 3: Descriptive statistics, Jarque-Bera normality test statistic and p-value, and KPSS unit root test statistics for the BTC price, BTC log-returns and for the seven technical oscillators.

As expected, Bitcoin prices are not stationary but their log-returns are stationary, and so are the seven technical oscillators. Interestingly, the oscillators are not normally distributed, but their empirical skewness estimates are close to zero and their empirical kurtosis close to 3.

## 4.2 Trading performance of each model

We report in Table 4 the previous evaluation metrics for all seven trading strategies to have an idea of their relative performances. Table 4 also reports the test for equality of each Sharpe ratio to zero in case of not independent and identically distributed elliptical returns, see Pav (2021, chapter 3) for more details. Moreover, it also reports the test by Wright et al. (2014) for the equality of all Sharpe ratios, which holds under the general assumption that the excess returns are stationary and ergodic.

Figures A1-A7 in the Appendix B reports the technical oscillators computed for each trading strategy, the bitcoin (BTC) price, the cumulative profit/loss, the long and short thresholds computed using the 5% and 95% quantiles of the technical oscillators, respectively, and the long and short orders. Note that a short order imply that that all previously bought bitcoins must be sold at that time.

<i>Strategy</i>	<i>Net.Trading.PL</i>	<i>Max.Drawdown</i>	<i>Max.Equity</i>	<i>Min.Equity</i>	<i>Ann.Sharpe</i>	<i>Profit.To.Max.Drawdown</i>	<i>Num.Txns</i>
<i>NVTS</i>	86,002	-97,656	147,472	-1,126	0.31	0.88	38
<i>NVRV</i>	46,685	-35,065	61,577	-574	0.41*	1.33	15
<i>NVHR</i>	37,728	-55,538	47,901	-7,636	0.20	0.68	17
<i>NVML</i>	43,439	-18,847	50,224	-2,739	0.47*	2.3	20
<i>NVOL</i>	45,589	-41,460	53,747	-2,877	0.30	1.1	18
<i>INET</i>	49,862	-16,249	58,375	0	0.55**	3.07	104
<i>VOLT</i>	24,424	-74,012	52,552	-20,116	0.12	0.33	16

Wright et al. (2014) test for the equality of all Sharpe ratios. P-value: 0.57

\*\* Significantly different from zero at the 5% probability level.

\* Significantly different from zero at the 10% probability level.

Table 4: Selected evaluation metrics for all trading strategies.

The NVTS strategy had the largest net trading profit, but also the largest max drawdown. Considering it had also the largest floating profit during the trading period, probably its performance could be improved using a profit-taking strategy: given that this goes beyond the scope of this work, we leave it as an avenue of further work.

Another interesting strategy is the one using the Network value Metcalfe’s law (NVML), which has a high Sharpe ratio, a low max drawdown of -18,857 USD (approximately 4% of the initial capital), and the second highest profit to max drawdown equal to 2.3. The strategy using the Network value Odlyzko’s law (NVOL) has performance metrics that are rather similar to the strategy using the network value Metcalfe’s law, even though they are generally slight worse than the latter. Moreover, the max drawdown and the profit to max drawdown (1.10) are much worse than the approach using the Metcalfe’s law.

The strategy that employed the network value to realized value (NVRV) ratio had a more balanced performance than the NVTS model. However, it requires a good fine-tuning of the moving averages’ parameters because this model tends to generate trading signals one to three weeks in advance.

The Network value to hash rate (NVHR) ratio provided good long-side entry signals but poor short signals, so this model must be used in conjunction with other strategies to determine when to exit the



market: we leave this issue as an avenue of further work.

On the other side of the spectrum, the VOLT model had the worst performance measures in almost all cases: interestingly, this model experienced also the largest floating losses during the trading period, thus highlighting that it is not effective in creating short trading signals.

Finally, the modified INET model showed the lowest drawdown, no floating losses during the trading period, the highest profit to max drawdown ratio, and it was the only strategy with a Sharpe ratio statistically different from zero at the 5% probability level. This empirical evidence make this trading strategy one of the most interesting considered so far. However, despite all these differences, we remark that the test by Wright et al. (2014) did not reject the null hypothesis that the annualized Sharpe ratios of all strategies are equal.

The empirical evidence seems to confirm the past successes of the INET model and the Metcalfe's law. The variant of the INET model that we presented in section 3.5 is particularly useful to quickly measure any change in the speculation activity, which makes it an interesting tool for short-term trading. Its main limit is probably the large number of transactions involved, which may results in a large number of transaction fees to pay and much lower trading profits. However, given that several crypto-exchanges have recently launched zero trading fees for spot trading (most notably, Binance and Bybit), this issue may be less problematic than it was in the past. As for Metcalfe's law, it is known since the work by Alabi (2017) that blockchain networks can be fairly well modeled by Metcalfe's Law, which identifies the value of a network as proportional to the square of the number of its nodes, or end users. Moreover, it is a useful model to identify potential price bubbles when the market price deviates too much from the underlying model and is not accompanied by any significant increase in the number of participating users, or any other development that could explain the higher market prices. Our back-testing results for trading purposes appear to confirm this past evidence.

## 5 Robustness checks

### 5.1 Trading performances in different time samples

We considered the performances of the previous trading strategies in different time samples to better understand their dynamics in different market situations. In this regard, we followed an increasing literature that has showed that there was a financial bubble in bitcoin prices in 2016-2017 that burst at the end of 2017, see Fry (2018), Corbet et al. (2018), Gerlach et al. (2019), and Xiong et al. (2020). Moreover, there is also a debate on whether the introduction of bitcoin futures in December 2017 crashed the market prices, see Köchling et al. (2019), Liu et al. (2020), Fantazzini and Kolodin (2020), Baig et al.

(2020), Jalan et al. (2021), Hattori and Ishida (2021), and Fantazzini (2022). Following this evidence, we divided our dataset into two sub-samples consisting of data before and after 10 December 2017, which is the day when the first bitcoin futures were introduced on the CBOE. Tables 5 and 6 show the evaluation metrics for all seven trading strategies in these two sub-samples. We remark that all open long positions were closed on December 9, 2017 in the first sample, and on March, 30 2022 in the second sample.

<i>Strategy</i>	<i>Net.Trading.PL</i>	<i>Max.Drawdown</i>	<i>Max.Equity</i>	<i>Min.Equity</i>	<i>Ann.Sharpe</i>	<i>Profit.To.Max.Drawdown</i>	<i>Num.Txns</i>
<i>NVTS</i>	14412	-5070	14748	-1139	0.97**	2.84	20
<i>NVRV</i>	10575	-2078	12653	-539	0.87**	5.08	5
<i>NVHR</i>	4928	-1247	5334	-309	0.99**	3.94	11
<i>NVML</i>	1348	-855	2195	-171	0.52*	1.57	8
<i>NVOL</i>	1078	-719	1755	-512	0.40	1.49	9
<i>INET</i>	8798	-2078	10876	0	0.72**	4.23	63
<i>VOLT</i>	-109	-690	147	-547	-0.08	-0.16	4

Wright et al. (2014) test for the equality of all Sharpe ratios. P-value: 0.10

\*\* Significantly different from zero at the 5% probability level.

\* Significantly different from zero at the 10% probability level.

Table 5: Selected comparison of trading strategies: **17-08-2011 / 09-12-2017**

<i>Strategy</i>	<i>Net.Trading.PL</i>	<i>Max.Drawdown</i>	<i>Max.Equity</i>	<i>Min.Equity</i>	<i>Ann.Sharpe</i>	<i>Profit.To.Max.Drawdown</i>	<i>Num.Txns</i>
<i>NVTS</i>	32014	-36974	33052	-6059	0.47	0.87	12
<i>NVRV</i>	32119	-32552	52609	-2009	0.53	0.98	6
<i>NVHR</i>	27986	-48321	52183	-1360	0.35	0.58	7
<i>NVML</i>	60025	-22965	64808	-6758	0.77*	2.61	11
<i>NVOL</i>	67803	-65104	99413	-6675	0.51	1.04	10
<i>INET</i>	25554	-18611	28727	-4749	0.50	1.37	58
<i>VOLT</i>	35319	-97656	87840	-11490	0.21	0.36	8

Wright et al. (2014) test for the equality of all Sharpe ratios. P-value: 0.87

\*\* Significantly different from zero at the 5% probability level.

\* Significantly different from zero at the 10% probability level.

Table 6: Selected comparison of trading strategies: **10-12-2017 / 30-03-2022.**

The two samples show quite different results: the first data sample up to the end of 2017 is characterized by low drawdowns, very large profit to max drawdown ratios, and Sharpe ratios that are significantly different from zero. Instead, the second sample has much larger drawdowns, very small profit to max drawdown ratios, and Sharpe ratios that are not significantly different from zero in almost all cases. Therefore, these results seem to indirectly confirm the findings by Köchling et al. (2019), Baig et al. (2020), and Ruan et al. (2021) who showed that the introduction of bitcoin futures in December 2017 improved the efficiency of bitcoin markets.

## 5.2 Trading performances with different thresholds

We also performed a sensitivity analysis where we changed the thresholds of the trading strategies by a small amount (we used the 10% and 90% quantiles, instead of the 5% and 95% quantiles) and we examined how the results changed compared to the baseline case. Table 7 shows the evaluation metrics for all seven trading strategies with the modified thresholds to generate buy and sell signals.

<i>Strategy</i>	<i>Net.Trading.PL</i>	<i>Max.Drawdown</i>	<i>Max.Equity</i>	<i>Min.Equity</i>	<i>Ann.Sharpe</i>	<i>Profit.To.Max.Drawdown</i>	<i>Num.Txns</i>
<i>NVTS</i>	90,167	-84,680	131,147	-1,825	0.36	1.06	51
<i>NVRV</i>	56,476	-78,834	94,966	-2749	0.24	0.72	20
<i>NVHR</i>	58,045	-17,061	58,434	-7,471	0.59**	3.40	26
<i>NVML</i>	64,323	-26,204	65,491	-2,788	0.45*	2.45	24
<i>NVOL</i>	65,536	-80,873	104,576	-7,520	0.29	0.81	24
<i>INET</i>	38,272	-18,715	49,711	-1,415	0.39**	2.04	238
<i>VOLT</i>	8,171	-80,873	48,166	-32,706	0.04	0.10	17

Wright et al. (2014) test for the equality of all Sharpe ratios. P-value: 0.36

\*\* Significantly different from zero at the 5% probability level.

\* Significantly different from zero at the 10% probability level.

Table 7: Selected comparison of trading strategies: **10% and 90% quantiles**

The smaller quantiles made the trading strategies more aggressive and involved a higher number of transactions. However, the effects were not homogenous across the competing strategies: the NVTS, NVRV, NVML and the NVOL models show higher final trading profits and maximum floating profits, but also much worse max drawdowns compared to the baseline case. The NVHR ratio was the only model that significantly improved all the evaluation metrics, whereas the INET and VOLT models worsened all metrics. In general, it appears that an optimization of the thresholds used to create buy and sell signals could potentially improve the models' performances. However, this goes beyond the scope of this paper and we leave it as an avenue for further research.

## 6 Discussion and Conclusions

This paper investigated the trading performances of several technical oscillators created using crypto assets pricing methods for short-term bitcoin trading. More specifically, we employed seven pricing models proposed in the professional and academic literature to create technical oscillators for daily trading. Two thresholds based on the quantiles of these oscillators were then used to generate buy and sell signals. The empirical back-testing analysis showed that some of these methods proved to be profitable with good Sharpe ratios and limited max drawdowns. However, the trading performances of several methods significantly worsened after 2017, thus indirectly confirming an increasing financial literature that showed that the introduction of bitcoin futures in 2017 improved the efficiency of bitcoin markets.

The strategy using the Network-to-transactions ratio (NVT) model had both the largest profit and the max drawdown: if it were combined with a profit-taking strategy, its performance could improve considerably, so we leave this issue as an avenue for further study.

The strategy that employed the network value to realized value (NVRV) ratio had a more balanced performance than the NVT model. In general, this model generated trading signals one to three weeks in advance, so we delayed the trade signals in our back-testing analysis with a 14-day moving average. If

this model were used in actual trading, the parameters of the moving average would have to be optimized to better synchronize the trading signals with asset price movements.

The Network value to hash rate (NVHR) ratio provided good long-side entry signals but poor short signals, so this model must be used in conjunction with other strategies to determine when to exit the market.

The strategy based on the network value to Metcalfe's law (NVML) ratio provided one of the few statistically significant Sharpe ratios, a low max drawdown and a high profit to max drawdown, thus showing to be suitable for long-term investment. In this regard, we note that this was the only strategy that improved its trading performance after the introduction of bitcoin futures in December 2017. The strategy using the network value to Odlyzko's law (NVOL) ratio had similar metrics to the NVML ratio, but its max drawdown and profit to max drawdown were much worse and, in general, its metrics worsened after 2017.

A variant of the Chris Burniske's (2017) INET modified for short-term trading had the lowest max drawdown and the highest annualized Sharpe ratio for the whole sample. However, its performance worsened considerably after 2017. Finally, the VOLT model had the worst performance for almost all metrics and in all time samples: this model was found to be good in generating long signals, but bad in generating short signals.

Our empirical analysis offers two conclusions. First, it confirmed again the importance of Metcalfe's Law for valuing crypto assets, according to which the value of a network is proportional to the square of the number of users. Metcalfe's Law has been usually employed for long-term evaluation and to identify potential price bubbles when the market price deviated too much from the underlying fundamental level. However, our back-testing results showed that such an approach can also be useful for short-term trading in different market conditions. Second, the bitcoin market has become more efficient since the introduction of futures trading at the end of 2017, and traders must be able to endure much larger drawdowns if they want to have significant trading profits. Needless to say, not all traders may have such possibility because "*the market can remain irrational longer than you can remain solvent*", as John Maynard Keynes supposedly once said in the 1930s<sup>6</sup>.

We remark that this increase in market efficiency after 2017 resulted in the stabilization of the number of Bitcoin active addresses per day (around 900,000) and in the number of confirmed transactions per day (around 250,000). Unfortunately, it did not affect Bitcoin electricity consumption, which has kept on slowly increasing over time, despite improvements in the mining equipment energy efficiency and a

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<sup>6</sup>There is now an open debate about the origin of this quote, given that there is evidence that this comment was possibly said by a financial advisor named Gary Shilling in 1986: "*In conclusion, this saying appeared in print by the 1986 and was closely associated with the financial analyst A. Gary Shilling. Based on current evidence it is likely that Shilling crafted of this apothegm. The evidence linking the quote to Keynes is very weak, and may be due to confusion with another saying attributed to Keynes as mentioned above*", <https://quoteinvestigator.com/2011/08/09/remain-solvent> .

more diverse energy mix, see the Cambridge Bitcoin Electricity Consumption Index (CBECI) provided by the University of Cambridge for more details (<https://ccaf.io/cbeci>). This apparent contradiction is due to the continuous increase in the Bitcoin hashrate (see [www.blockchain.com/explorer/charts/hash-rate](http://www.blockchain.com/explorer/charts/hash-rate)), for which several reasons have been proposed: for example, blockchain data analytics firm Glassnode believes that the *“hashrate rise is due to more efficient mining hardware coming online and/or miners with superior balance sheets having a larger share of the hash power network”*<sup>7</sup>. Sarkar (2022) suggested three additional reasons: falling mining rig prices, increasing crypto-friendly jurisdictions, and the Ethereum transition from a proof-of-work (PoW) to a proof-of-stake (PoS) consensus that forced Ethereum miners to sell off or repurpose their equipment toward mining Bitcoin. Whatever the real reasons are, increased trading is not one of them.

It is important to highlight also the limitations of this study: first of all, we did not try to optimize the parameters of the technical oscillators, given that the choice of specific model parameters may strongly vary across investors according to their risk-return profile. Moreover, we remark that a complete trading strategy requires not only trading signals, but also reliable trade management and stop-loss strategies: considering that almost all examined models proved to be profitable without the use of a stop-loss strategy, complete trading strategies for actual trading would have probably shown better performances. These additional issues are left as a possibility of future work.

Another limit of our analysis is the complete focus on Bitcoin. Even though it is still the most traded crypto-asset, its dominance has decreased over time (see e.g. [coinmarketcap.com/charts](https://coinmarketcap.com/charts)). An interesting avenue of further research would be to expand the analysis discussed in this paper with other crypto assets and with different variants of the technical indicators presented in this paper. Moreover, we did not consider transaction fees and short-sales. Even though there is a trend in decreasing fees over time across all crypto-exchanges, they can still affect trading profits. As for short-sales, they can improve net profits, but they also involve liquidation risks and can cause major losses. We leave all these issues as topics for future research.

Finally, we remark that the success of Metcalfe’s law for short-term trading makes an analysis using approaches based on Social Network Analysis a natural extension to understand the ultimate reasons behind the phenomena reported in this work. We leave this issue as an interesting avenue for further research.

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<sup>7</sup>See <https://insights.glassnode.com/the-week-onchain-week-40-2022> .

## References

- Alabi, K. Digital blockchain networks appear to be following Metcalfe's Law. *Electron. Commer. Res. Appl.* **2017**, *24*: 23-29
- Ao, Z.; Horvath, G.; Zhang, L. Are decentralized finance really decentralized? A social network analysis of the Aave protocol on the Ethereum blockchain. arXiv **2022**, arXiv:2206.08401.
- Baig, S.; Haroon, O.; Sabah, N. Price clustering after the introduction of bitcoin futures. *Appl. Financ. Lett.* **2020**, *9*, 36-42.
- Baumann, A.; Fabian, B.; Lischke, M. Exploring the Bitcoin Network. *WEBIST* **2014**, *1*, 369-374.
- Berengueres, J. Valuation of Cryptocurrency Mining Operations. *Ledger* **2018**, *3*, 60-67.
- Benetton, M.; Compiani, G.; Morse, A. Cryptomining: Energy use and local impact. University of California, Berkeley, 2019, working paper.
- Bonifazi, G.; Corradini, E.; Ursino, D.; Virgili, L. A Social Network Analysis-Based Approach to Investigate User Behaviour during a Cryptocurrency Speculative Bubble. *J. Inf. Sci.* **2021**, 01655515211047428.
- Bonifazi, G.; Corradini, E.; Ursino, D.; Virgili, L. Defining user spectra to classify Ethereum users based on their behavior. *J. Big Data* **2022**, *9(1)*, 1-39.
- Borgatti, S. P.; Everett, M. G.; Johnson, J. C. *Analyzing social networks*. Sage: London, 2018.
- Bovet, A.; Campajola, C.; Mottes, F.; Restocchi, V.; Vallarano, N.; Squartini, T.; Tessone, C.J. The evolving liaisons between the transaction networks of Bitcoin and its price dynamics. *arXiv* **2019**, arXiv:1907.03577.
- Burniske, Chris, and Jack Tatar. *Cryptoassets: The Innovative Investor's Guide to Bitcoin and Beyond*. McGraw-Hill: New York, 2018.
- Chang, T. H.; Svetinovic, D. Data analysis of digital currency networks: Namecoin case study. In *21st International Conference on Engineering of Complex Computer Systems (ICECCS)*, Nov 6-8, Dubai, United Arab Emirates. 2016, pp. 122-125.
- Coinmetrics. 2018. *Introducing Realized Capitalization*. Available at: <https://coinmetrics.io/realized-capitalization>. Accessed on July 1, 2022.
- Corbet, S.; Lucey, B.; Yarovaya, L. Datedstamping the bitcoin and ethereum bubbles. *Finance Res. Lett.* **2018**, *26*, 81-88
- Delgado-Mohatar, O.; Felis-Rota, M.; Fernández-Herraiz, C. The Bitcoin mining breakdown: Is mining still profitable? *Econ. Lett.* **2019**, *184*, 108492.
- Evans, Alex. 2018. On value, velocity and monetary theory: A new approach to cryptoasset valuations. *Medium*. Available at <https://web.archive.org/web/20210918091400/https://medium.com/blockchannel/on-value-velocity-and-monetary-theory-a-new-approach-to-cryptoasset-valuations-32c9b22e3b6f>, Accessed on July 1, 2022.
- Fantazzini, D. *Quantitative Finance with R and Cryptocurrencies*. Amazon KDP: Seattle, 2019, ISBN-13: 978-1090685315.
- Fantazzini, D. Crypto-Coins and Credit Risk: Modelling and Forecasting Their Probability of Death. *J. Risk Financ. Manag.* **2022**, *15(7)*: 304.
- Fantazzini, D.; Kolodin, N. Does the hashrate affect the bitcoin price? *J. Risk Financ. Manag.* **2020**, *13*, 263.
- Fantazzini, D.; Calabrese, R.. Crypto Exchanges and Credit Risk: Modeling and Forecasting the Probability of Closure. *J. Risk Financ. Manag.* **2021**, *14(11)*, 516.
- Fantazzini, D.; Zimin, S. A multivariate approach for the simultaneous modelling of market risk and credit risk for cryptocurrencies. *J. Ind. Bus. Econ.* **2020**, *47(1)*, 19-69.
- Ferretti, S.; D'Angelo, G. On the ethereum blockchain structure: A complex networks theory perspective. *Concurr. Comput. Pract. Exp.* **2019**, *32(12)*, e5493.
- Fry, J. Booms, busts and heavy-tails: The story of bitcoin and cryptocurrency markets? *Econ. Lett.* **2018**, *171*, 225-29.
- Hargrave, J.; Sahdev, N.; Feldmeier, O. How value is created in tokenized assets. In: *Blockchain Economics: Implications of Distributed Ledgers-Markets, Communications Networks, and Algorithmic Reality*, Melanie, S., Jason, P., Soichiro, T., Frank, W Paolo, T. eds.; 2019. Volume 1, World Scientific: New Jersey.
- García-Monleón, F.; Danvila-del-Valle, I.; Lara, F. Intrinsic value in crypto currencies. *Technol. Forecast. Soc. Change* **2021**, *162*, 120393.
- Gerlach, J.C.; Guilherme, D.; Sornette, D. Dissection of bitcoin's multiscale bubble history from January 2012 to February 2018. *Royal Soc. Open Sci.* **2019**, *6*, 180643.

Goutte, S.; Khaled, G.; Saadi, S. 2022. *Cryptofinance: A New Currency for A New Economy*. World Scientific: Singapore.

Gradojevic, N.; Kukolj, D.; Adcock, R.; Djakovic, V. Forecasting Bitcoin with technical analysis: A not-so-random forest? *Int. J. Forecast.* **2021**, in press.

Hattori, T.; Ryo, I. Did the introduction of bitcoin futures crash the bitcoin market at the end of 2017? *N. Am. J. Econ. Finance* **2021**, *56*, 101322.

Huang, J. Z.; Huang, W.; Ni, J. Predicting bitcoin returns using high-dimensional technical indicators. *J. Finance and Data Sci.* **2019**, *5(3)*, 140-155.

Huynh, T.; Luu, D. When Elon Musk Changes his Tone, Does Bitcoin Adjust Its Tune? *Comput. Econ.* **2022**, in press.

Kaal, W.; Evans, S.; Howe, H. Digital Asset Valuation. *University of St. Thomas (Minnesota) Legal Studies Research Paper* **2022**, No. 22-10, Available at SSRN: <https://ssrn.com/abstract=4033886>.

Kalichkin, D. Rethinking Network Value to Transactions (NVT) Ratio. *Medium*, 2018. Available at: <https://medium.com/cryptolab/https-medium-com-kalichkin-rethinking-nvt-ratio-2cf810df0ab0> . Accessed on July 1, 2022.

Köchling, G.; Müller, J.; Posch, P. Does the introduction of futures improve the efficiency of bitcoin? *Finance Res. Lett.* **2019**, *30*, 367–70.

Kondor, D.; Pósfai, M.; Csabai, I.; Vattay, G. Do the rich get richer? An empirical analysis of the Bitcoin transaction network. *PLoS one* **2014**, *9(2)*, e86197.

Kyriazis, N.; Papadamou, S.; Tzeremes, P.; Corbet, S. The differential influence of social media sentiment on cryptocurrency returns and volatility during COVID-19. *Q. Rev. Econ. Finance* **2022**, in press.

Jalan, A.; Matkovskyy, R.; Urquhart, A. What effect did the introduction of bitcoin futures have on the bitcoin spot market? *Eur. J. Finance* **2021**, *27*, 1251–81.

Jernej, D. *Approaches to Crypto Assets Valuation*. Master thesis, Ljubljana: University of Ljubljana, 2021.

Li, Y.; Islambekov, U.; Akcora, C.; Smirnova, E.; Gel, Y.R.; Kantarcioglu, M. Dissecting Ethereum Blockchain Analytics: What We Learn from Topology and Geometry of the Ethereum Graph? In *Proceedings of the 2020 SIAM International Conference on Data Mining*, Hilton Cincinnati, OH, USA, 7–9 May 2020; pp. 523–531.

Liang, J.; Li, L.; Zeng, D. Evolutionary dynamics of cryptocurrency transaction networks: An empirical study. *PLoS one* **2018**, *13(8)*, e0202202.

Liu, Y. Cryptocurrency Valuation, *Medium*, 2019. Available at: <https://medium.com/coinmonks/cryptocurrency-valuation-d9979074404> . Accessed on July 1, 2022.

Liu, Y.; Zhang, L. Cryptocurrency valuation: An explainable AI approach, *arXiv* **2022**, arXiv:2201.12893.

Liu, R.; Shanfeng, W.; Zili, Z.; Zhao, Z. Is the introduction of futures responsible for the crash of bitcoin? *Finance Res. Lett.* **2020** *34*, 101259.

Mahmudov, Murad, and Puell, David. Bitcoin Market-Value-to-Realized-Value (MVRV) Ratio. *Medium*, 2018. Available at: <https://medium.com/adaptivecapital/bitcoin-market-value-to-realized-value-mvr-ratio-3ebc914d8bae> . Accessed on July 1, 2022.

Metcalfe, B. Metcalfe’s law after 40 years of Ethernet. *Computer* **2013**, *46(12)*, 26-31.

Motamed, A.P.; Bahrak, B. Quantitative analysis of cryptocurrencies transaction graph. *Appl. Netw. Sci.* **2019**, *4(1)*, 1-21.

Nakano, M.; Takahashi, A.; Takahashi, S. Bitcoin technical trading with artificial neural network. *Phys. A: Stat. Mech. Appl.* **2018**, *510*, 587-609.

Odlyzko, A.; Briscoe, B.; Tilly, B. Metcalfe’s law is wrong-communications networks increase in value as they add members-but by how much? *IEEE Spectr.* **2006**, *43(7)*, 34-39.

Ortu, M.; Uras, N.; Conversano, C.; Bartolucci, S.; Destefanis, G. On technical trading and social media indicators for cryptocurrency price classification through deep learning. *Expert Syst. Appl.* **2022**, *198*, 116804.

Otte, E.; Rousseau, R. Social network analysis: a powerful strategy, also for the information sciences. *J. Inf. Sci.* **2002**, *28(6)*, 441-453.

Papadamou, S.; Kyriazis, N. A.; Tzeremes, P.; Corbet, S. Herding behaviour and price convergence clubs in cryptocurrencies during bull and bear markets. *J. Behav. Exp. Finance* **2021a**, *30*, 100469.

Papadamou, S.; Kyriazis, N. A.; Tzeremes, P. Non-linear causal linkages of EPU and gold with major cryptocurrencies during bull and bear markets. *N. Am. J. Econ. Finance* **2021b**, *56*, 101343.

Pav, S. *The Sharpe Ratio: Statistics and Applications*. Chapman and Hall/CRC: Boca-Raton, Florida, 2021.

Peterson, T. Metcalfe’s Law as a Model for Bitcoin’s Value. *Altern. Invest. Anl. Rev.* **2018**, *2*, 9-18

Romano, Y.; Patterson, E.; Candes, E. Conformalized quantile regression. *Adv Neural Inf Process Syst* **2019**, *32*, 3543–3553 .

Ruan, Q.; Lu, M.; Lv, D. Effect of introducing Bitcoin futures on the underlying Bitcoin market efficiency: A multi-fractal analysis. *Chaos Solit. Fractals* **2021**, *153*, 111576.

Romanchenko, O.; Shemetkova, O.; Piatanova, V.; Kornienko, D. Approach of estimation of the fair value of assets on a cryptocurrency market. In *The 2018 International Conference on Digital Science*, 2018, pp. 245-253. Springer, Cham.

Sabalionis, A.; Wenbo, W.; Park, H. What affects the price movements in Bitcoin and Ethereum? *Manch. Sch* **2021**, *89(1)*, 102-127.

Sarkar, A. Top 3 reasons why Bitcoin hash rate continues to attain new all-time highs. *Cointelegraph* **2022**, *October 9*. Available online: <https://cointelegraph.com/news/top-3-reasons-why-bitcoin-hash-rate-continues-to-attain-new-all-time-highs> (accessed on 12/11/2022).

Shapiro, C.; Varian, H. *Information rules: A strategic guide to the network economy*. Harvard Business Press: Boston, 1998.

Stylianou, K.; Spiegelberg, L.; Herlihy, M.; Carter, N. Cryptocurrency Competition and Market Concentration in the Presence of Network Effects. *Ledger* **2021**, *6*, 81-101.

Thum, M. The economic cost of bitcoin mining. *CESifo Forum* **2018**, *19(1)*, 43-45.

Vallarano, N.; Tessone, C. J.; Squartini, T. Bitcoin Transaction Networks: an overview of recent results. *Front. Phys.* **2020**, *8*, 286.

Wasserman, S.; Faust, K. *Social network analysis: Methods and applications*. Cambridge University Press: Cambridge, 1994.

Wonder, Awe. Introducing The Bitcoin "MVRV Z" Metric That Predicts Market Tops with 90%+ Accuracy. *Medium*, 2018. Available at: [https://medium.com/@Awe\\_andWonder/introducing-the-bitcoin-mvr-v-z-score-metric-that-predicts-market-tops-with-90-accuracy-89d90df043d7](https://medium.com/@Awe_andWonder/introducing-the-bitcoin-mvr-v-z-score-metric-that-predicts-market-tops-with-90-accuracy-89d90df043d7) . Accessed on July 1, 2022.

Woo, Willy. 2017. Is Bitcoin In A Bubble? Check The NVT Ratio. *Forbes*, Available at: <https://www.forbes.com/sites/wwoo/2017/09/29/bitcoin-in-a-bubble-check-the-nvt-ratio> . Accessed on July 1, 2022.

Woo, Willy. 2018. *Bitcoin NVT Signal*. Available at: <http://charts.woobull.com/bitcoin-nvt-signal> . Accessed on July 1, 2022.

21Shares. 2020. *Valuing Bitcoin*. Available at: <https://cdn.21shares.com/img/uploads/valuing-bitcoin-07-2020.pdf> . Accessed on July 1, 2022.

Wright, J.; Yam, S.; Yung, S. A test for the equality of multiple Sharpe ratios. *Journal of Risk* **2014**, *16(4)*, 3-21.

Yang, S.; Keller, F.B.; Zheng, L. *Social network analysis: Methods and examples*. Sage Publications: London 2016.

Xiong, J.; Liu, Q.; Zhao, L. A new method to verify bitcoin bubbles: Based on the production cost. *N. Am. J. Econ. Finance* **2020**, *51*, 101095.

21Shares. 2020. *Valuing Bitcoin*. 21Shares. Available at: <https://21shares.com/research/valuing-bitcoin/> Accessed on July 1, 2022.



## Appendix A: Data sources

1. *Price data*: this is free data and the source is as follows:

<https://studio.glassnode.com/metrics?a=BTC&category=&m=market.PriceUsdClose>

2. *Network value*: this is free data and the source is as follows:

<https://studio.glassnode.com/metrics?a=BTC&category=&m=market.MarketcapUsd>

3. *Realized value*: this is not free data and the source is as follows:

<https://studio.glassnode.com/metrics?a=BTC&category=&m=market.MarketcapRealizedUsd>

4. *Active addresses*: this is free data and the source is as follows:

<https://studio.glassnode.com/metrics?a=BTC&category=&m=addresses.ActiveCount>

5. *Network hashrate*: this is free data and the source is as follows:

<https://studio.glassnode.com/metrics?a=BTC&category=&m=mining.HashRateMean>

6. *Transaction in exchange*: this is not free data and the source is as follows:

<https://studio.glassnode.com/metrics?a=BTC&category=&m=transactions.TransfersVolumeWithinExchangesSum>

7. *Risk-free rate*: this is free data and the source is as follows:

<https://fred.stlouisfed.org/series/GS10>

## Appendix B: Trading Strategies performances

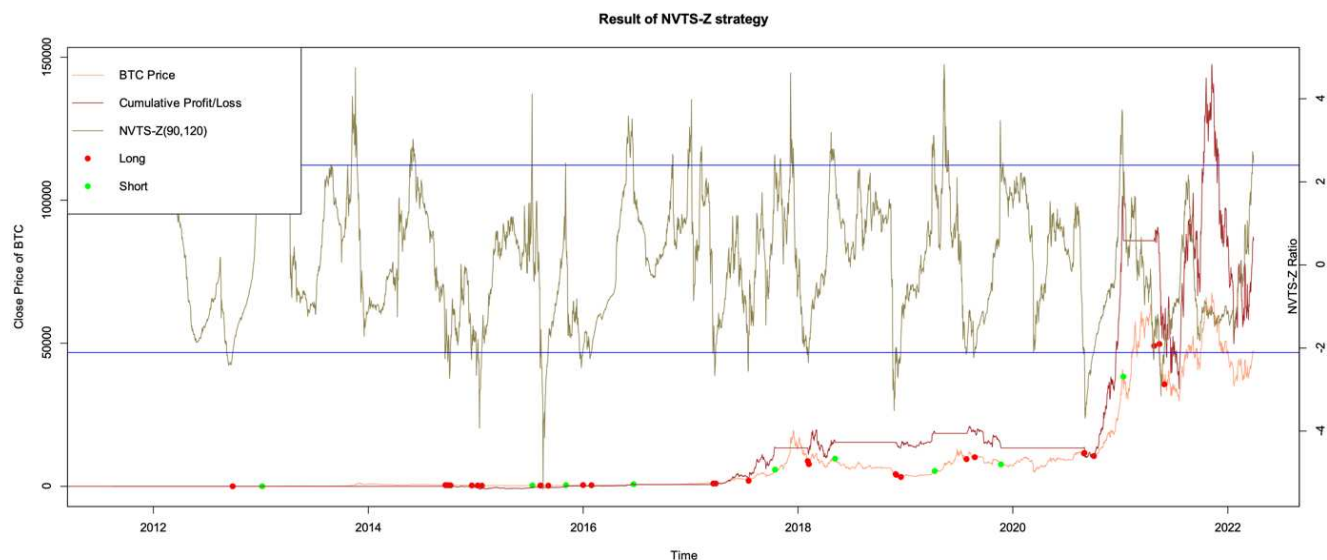


Figure 8: NVTS-Z strategy: BTC price (orange line, left-hand-side), cumulative profit/loss (red line, left-hand-side), NVTS-Z ratio (brown line, right-hand-side), long and short thresholds (blue lines, right-hand-side), long orders (red points) and short orders (green points).

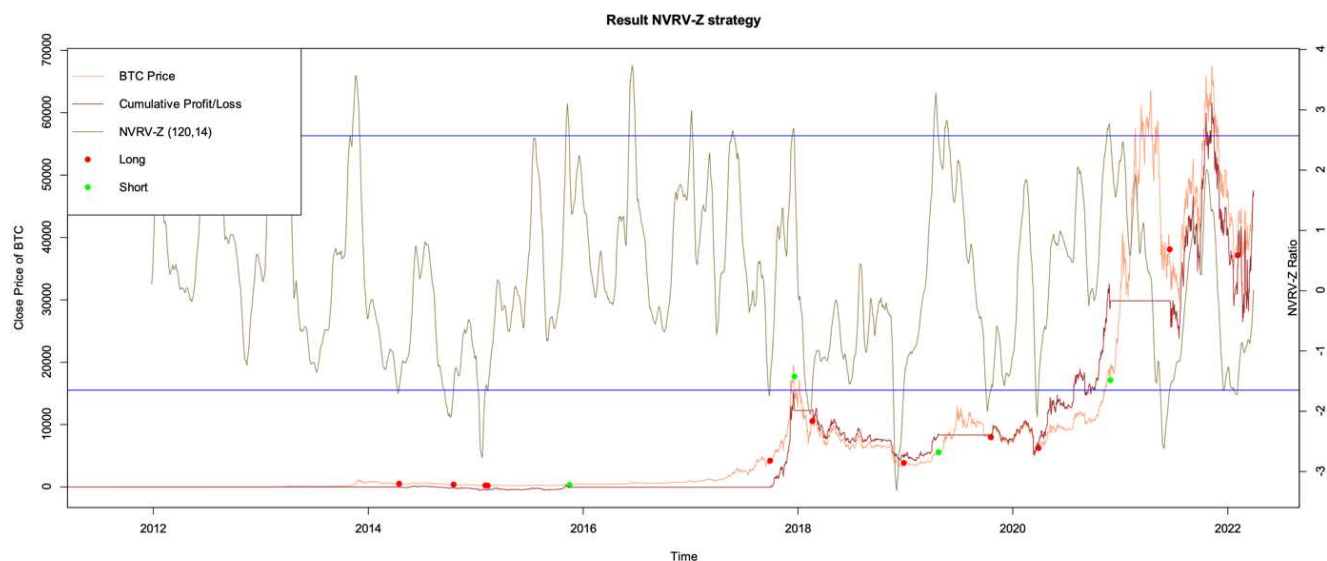


Figure 9: NVRV-Z strategy: BTC price (orange line, left-hand-side), cumulative profit/loss (red line, left-hand-side), NVRV-Z ratio (brown line, right-hand-side), long and short thresholds (blue lines, right-hand-side), long orders (red points) and short orders (green points).

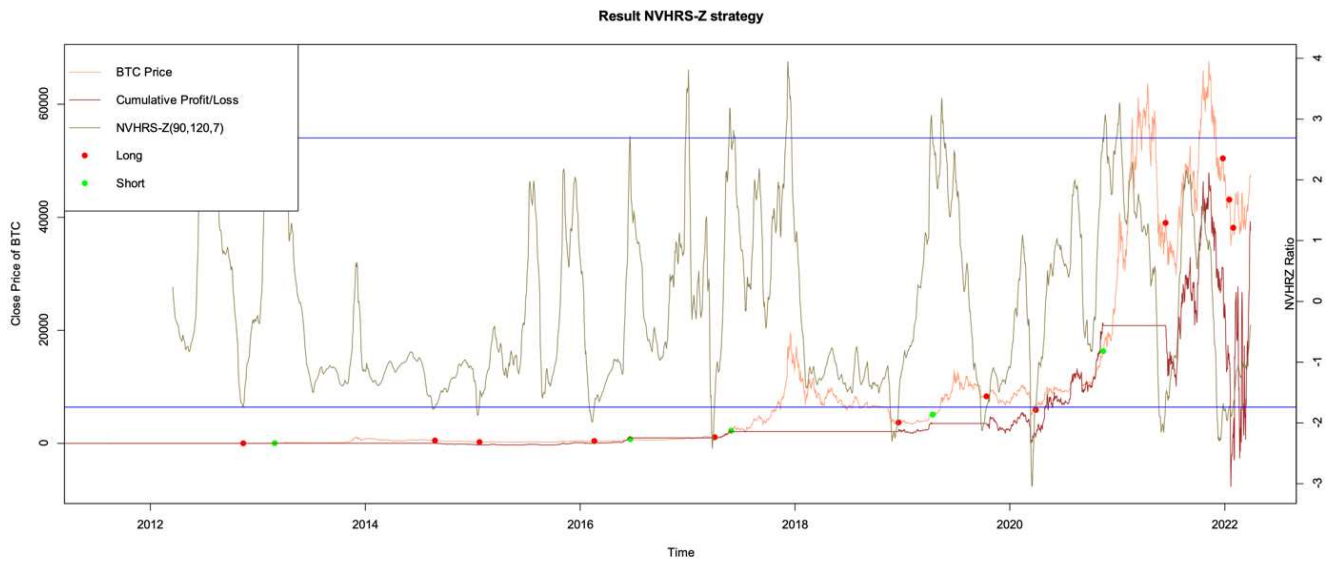


Figure 10: NVHRS-Z strategy: BTC price (orange line, left-hand-side), cumulative profit/loss (red line, left-hand-side), NVHRS-Z ratio (brown line, right-hand-side), long and short thresholds (blue lines, right-hand-side), long orders (red points) and short orders (green points).

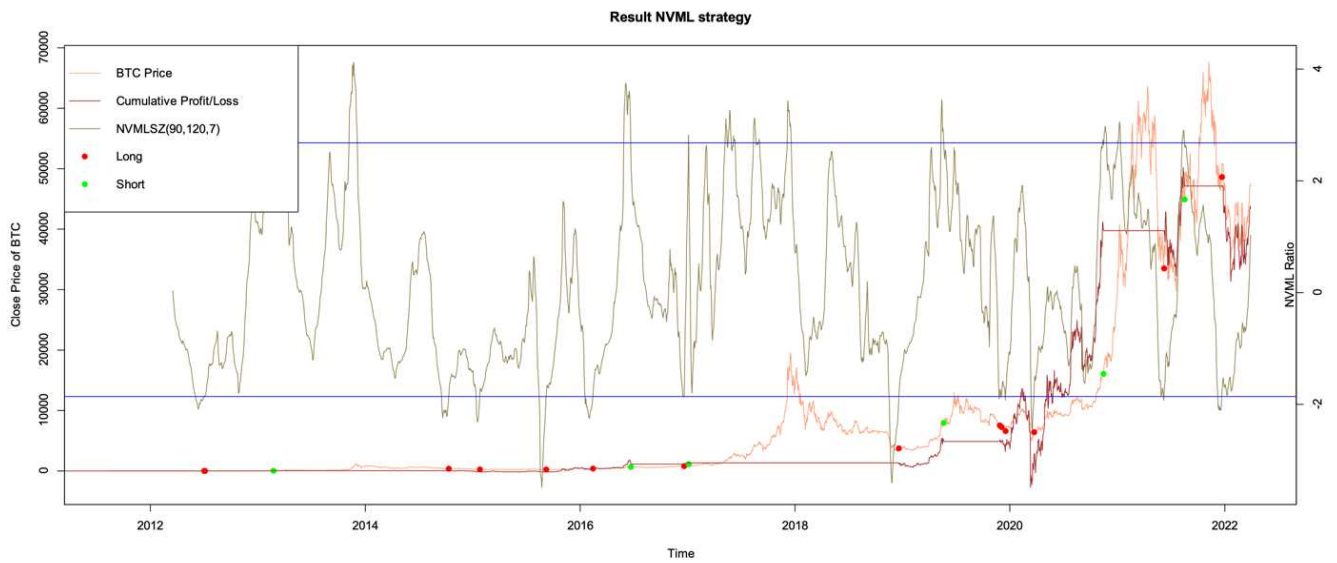


Figure 11: NVMLS-Z strategy: BTC price (orange line, left-hand-side), cumulative profit/loss (red line, left-hand-side), NVMLS-Z ratio (brown line, right-hand-side), long and short thresholds (blue lines, right-hand-side), long orders (red points) and short orders (green points).

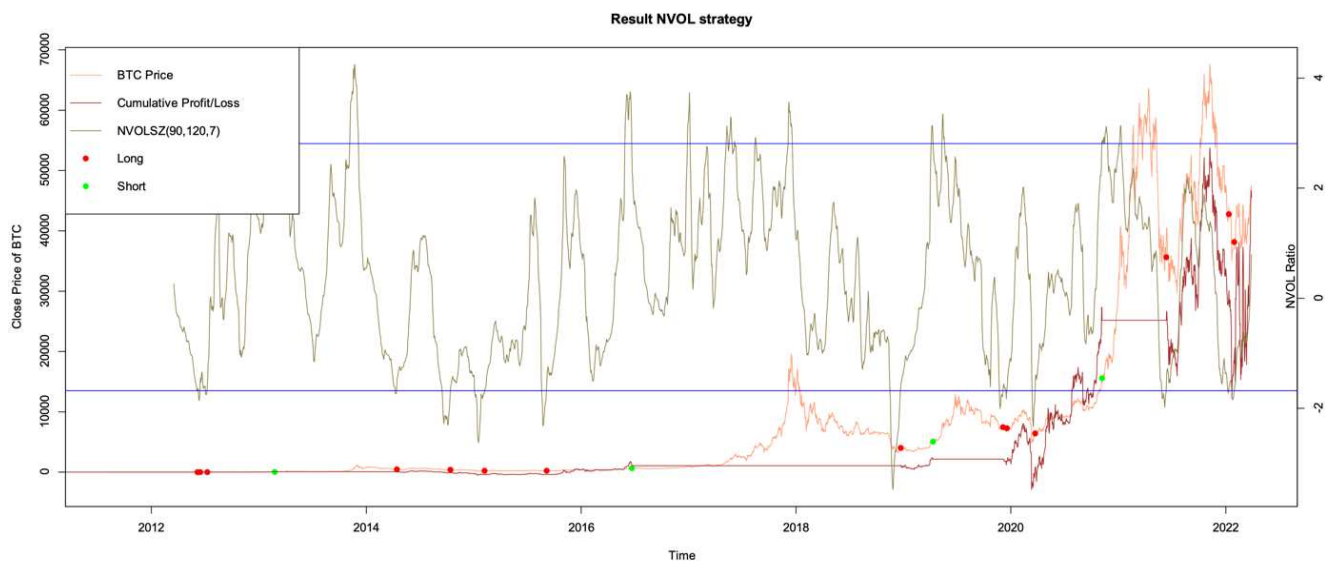


Figure 12: NVOLS-Z strategy: BTC price (orange line, left-hand-side), cumulative profit/loss (red line, left-hand-side), NVOLS-Z ratio (brown line, right-hand-side), long and short thresholds (blue lines, right-hand-side), long orders (red points) and short orders (green points).

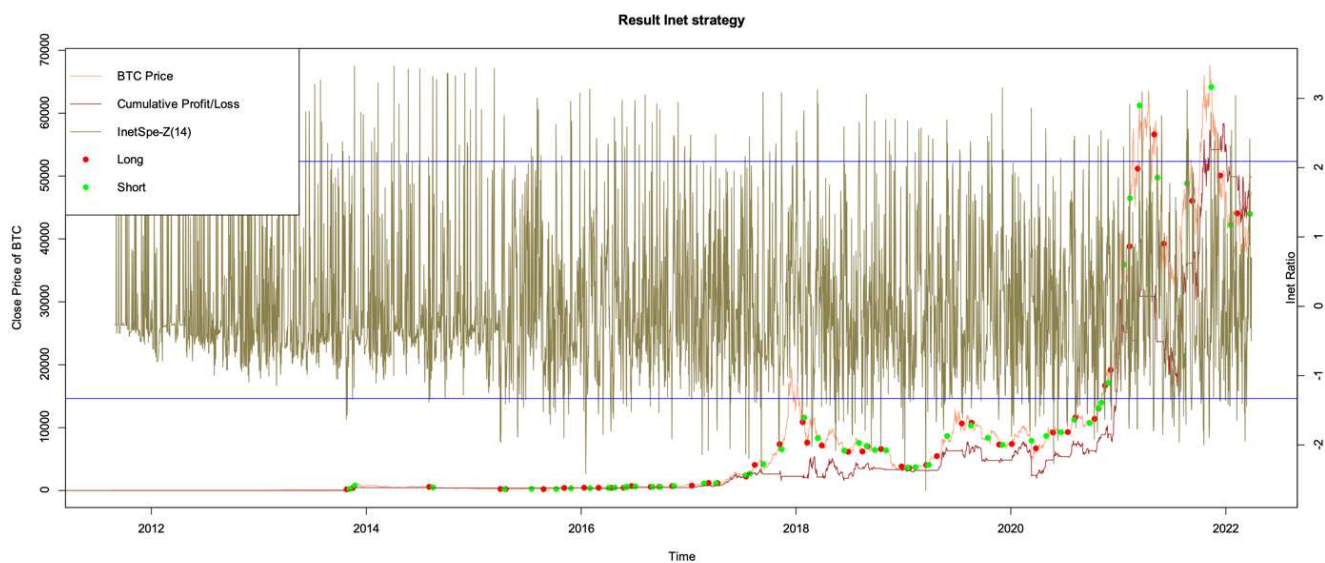


Figure 13: InetSpe-Z strategy: BTC price (orange line, left-hand-side), cumulative profit/loss (red line, left-hand-side), InetSpe-Z ratio (brown line, right-hand-side), long and short thresholds (blue lines, right-hand-side), long orders (red points) and short orders (green points).

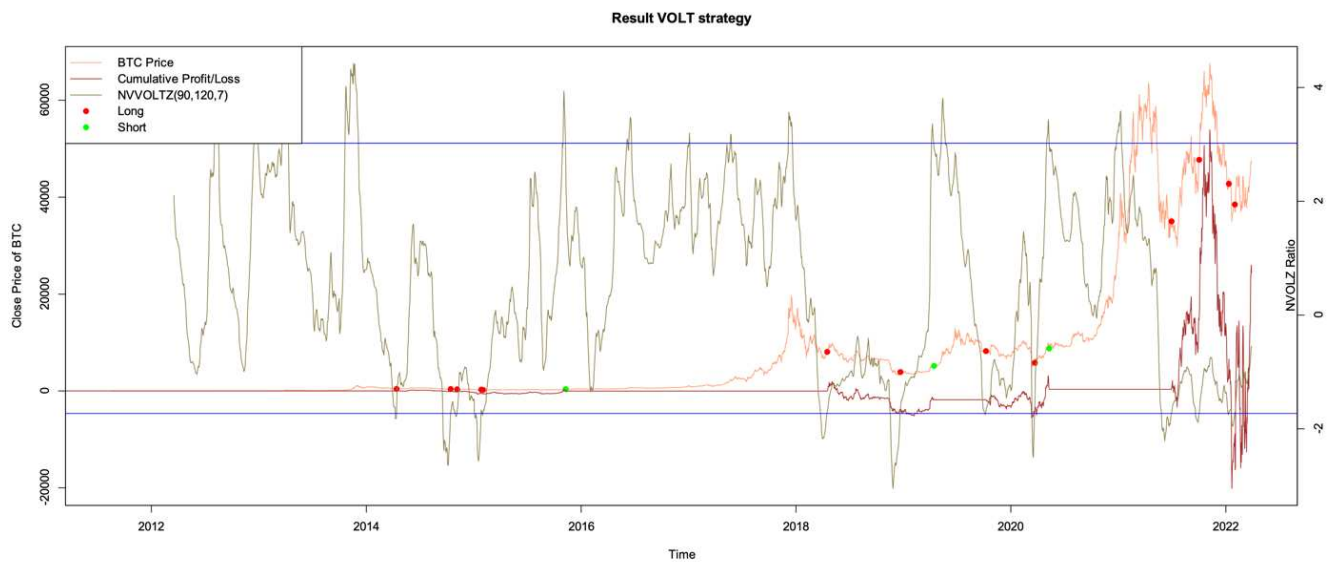


Figure 14: VOLT strategy: BTC price (orange line, left-hand-side), cumulative profit/loss (red line, left-hand-side), VOLT ratio (brown line, right-hand-side), long and short thresholds (blue lines, right-hand-side), long orders (red points) and short orders (green points).