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Using Crypto-Asset 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-asset 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

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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 offering a major defense against data tampering. A "miner" records the new transactions information and transfers them into a block and then must solve a complex mathematical puzzle named proof-of-work (PoW), which is a decentralized consensus mechanism that is employed to prevent anyone 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 Bitcoins to be issued is limited to 21 million, and this number will be reached around 2140.

Bitcoin and thousands of other crypto-assets are traded daily on a large number of crypto-exchanges (at the end of the first quarter of 2022, there were almost 300 exchanges, see, for example, coinmarketcap.com/rankings/exchanges, accessed on 1 July 2022), with a total daily trading volume that, on some days, was higher than 100 billion dollars. In this regard, several methods have been proposed to estimate the fundamental value of Bitcoin; see [1–3] for an introduction at the textbook level. There is also 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., Refs. [4–7], and references therein.

In this work, we followed in the footsteps of [8,9], 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 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 shows 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 [10–12] for a detailed discussion.

The rest of this paper is organized as follows. Section 2 reviews the literature devoted to crypto-asset 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 [3], chapter 9, for a larger review.

2.1. Cost Analysis

Ref. [13] performed a valuation of several crypto coins by using the net present value. They 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. Ref. [14] analyzed the cost of a single miner, assuming that a new miner enters into 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.

Ref. [15] 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 $1952. Instead, Ref. [16] 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

Ref. [17] 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.

Ref. [18] 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; a typical example is Bitcoin. Platform tokens can be used to run transactions and smart connections on the blockchain; 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). Ref. [18] 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 Metcalfe's law is appropriate for measuring the value of crypto coins (more about this topic below).

Ref. [19] 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, Ref. [20] 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 Crypto-Asset Modeling

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 [21] for an introductory survey or [22–24] for a discussion at the textbook level.

There is an increasing body in 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 [25–31], just to name a few.

The network structures may differ significantly across blockchains: for example, Ref. [32] 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, Ref. [33] 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 [29] showed that the price of Bitcoin is negatively correlated with the average outdegree (the outdegree is the number of edges that are directed out of a node in the directed network graph). Ref. [34] 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 [35] built an ARIMA time-series model to forecast price anomalies using network features. Finally, Ref. [36] presented an SNA-based approach to investigate user behavior during the speculative bubble involving Ethereum in 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

Ref. [37] 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, 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.

Ref. [38] 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 at 50 lire until 1980, 100 lire until 1984, and 200 lire from 1984. It remained at this value until the introduction of the euro in 2001 in Italy, and it has 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%.

Ref. [39] discussed the intrinsic values for different type of cryptocurrencies, including initial coin offerings (ICOs) and 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 cryptocurrency 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. Ref. [39] 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-layer coins, given that PayPal, Visa, and crypto-coin networks all possess similar characteristics.

Ref. [40] 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.

Ref. [41] 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 from 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 trend in the literature towards investigating 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 [42–44] and references therein.

2.5. Ratios of Crypto Coins

The network-value–transaction (*NVT*) ratio first made its appearance in February 2017 in a tweet but was discussed in more detail in an article published on Forbes later in 2017 by [45]. Ref. [9] later improved the *NVT* ratio by proposing the *NVTS* (*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 *NVTS* ratio, Ref. [46] proposed the market-value–realized-value (MVRV) ratio, which is the market value divided by the realized value. The market value is the last known price multiplied by the current circulating supply, while the realized value considers the lost and unmoved Bitcoins and is calculated by summing the products of price per bitcoin and what is called the "Unspent Transaction Output" (UTXO). By dividing the market value by the realized value, an indication of Bitcoin's real value emerges: [46] found that, historically, a MVRV ratio above 3.7 denotes overvaluation, whereas a MVRV ratio below one indicates undervaluation.

Refs. [47,48] 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) ratio is not a good crypto-coin indicator, and they highlighted the limitations of the network-value–transaction (*NVT*) ratio, which ignores the store-of-value function. Given this evidence, they proposed a new ratio called the price–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 ratios such as these 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 [3].

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-asset 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-asset pricing methods, and we discuss in detail how to use them to create technical oscillators and buy-and-sell trading signals.

3.1. Network-Value–Transaction Ratio (NVT)

The network-value–transaction (*NVT*) ratio was originally proposed by [45] as follows:

$$NVT = \frac{Network\ Value}{Transaction\ Value} = \frac{Market\ Capitalization}{Transaction\ Value} \tag{1}$$

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–earnings (PE) ratio, which is a traditional method used in financial analysis. If the *NVT* ratio is too high, such that the network value is much greater than the total transferred on-chain value for a specific period, then the market is overvalued and has high expectations for the 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,

$$Market\ Capitalization = Supply_{Token} \times Price_{Token}$$

$$Transaction\ Value = Transaction\ Volume_{Token} \times Price_{Token}$$

And we substitute them into the *NVT* ratio, we obtain

$$NVT = \frac{Supply_{Token} \times Price_{Token}}{Transaction\ Volume_{Token} \times Price_{Token}} = \frac{Supply_{Token}}{Transaction\ Volume_{Token}}$$

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

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

The *NVT* ratio is very volatile, so using this ratio as an indicator is rather difficult. To solve this problem, Ref. [9] modified the ratio (1) as follows:

$$NVTS = \frac{Network\ Value}{MA_{Transaction\ Value}} \tag{2}$$

where he used the moving average (MA) of the transaction value to smooth the *NVT* ratio. Ref. [8] modified Kalichkin's *NVTS* model (2) to what he called the "adjusted-*NVTS* ratio", which is an oscillator indicator able to generate buy and sell signals. However, he did not provide any formula, simply stating 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*" [8]. Therefore, it appears that he used the well-known z-score to standardize the *NVTS* ratio as

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

where μ is the mean value of the *NVTS* ratio computed over a specific period of time b (with b = 2 years), σ is the standard deviation over the same period b, and a is the time sample used to compute the moving average of the network transaction value in Equation (2).

3.2. Network-Value–Realized-Value Ratio (NVRV)

The network-value–realized-value (*NVRV*) ratio was first introduced by [46] and is computed as follows:

$$NVRV = \frac{Network\ Value}{Realized\ Value} \tag{4}$$

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

$$Network\ Value = Last\ trade\ coin\ price \times All\ coins\ in\ circulation$$

$$Realized\ Value = \sum_i Last\ trade\ price\ of\ each\ coin_i$$

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 [49] 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 [50]:

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

where μ is the mean value of the *NVRV* ratio computed over a specific period of time b, σ is the standard deviation over the same period b, and a is the time sample used to compute the moving average of the *NVRV* in Equation (4).

3.3. Network-Value–Hashrate Ratio (NVHR)

The network-value to hashrate ratio measures a crypto-asset network value in dollars per unit of hashrate, see [51] 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 like so:

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

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

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

where μ is the mean value of the *NVHR* ratio computed over a specific period of time b, σ is the standard deviation over the same period b, and 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:

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

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 [51]. 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 [52,53] 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 like so:

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

where A is a coefficient and n is the number of connected system users. Ref. [54] 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–Metcalfe's Law Ratio

If we assume that Metcalfe's law for crypto coins can be approximated as

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

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 by

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

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

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

where μ is the mean value of the $NVML$ ratio computed over a specific period of time b, σ is the standard deviation over the same period b, and 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:

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

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

3.4.2. Network-Value–Odlyzko's Law Ratio

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

$$OL \cong Active\ Addresses * \log(Active\ Addresses)$$

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

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

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

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

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

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

where μ is the mean value of the $NVML$ ratio computed over a specific period of time b, σ is the standard deviation over the same period b, and 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:

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

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 [55] 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:

$$M_0 V = PQ = Y$$

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 obtain

$$Y = Transfer\ Value\ for\ consumers = P_{\$} * M_C$$

where M_C is the total transferred coins on-chain for consumption, while $P_{\$}$ 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 monetary-based crypto-coin value in US dollars $M_{0\$}$,

$$M_{0\$}V = \frac{M_{0\$}}{NVT} = P_{\$} \times M_C \Rightarrow$$

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

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

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

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:

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

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

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 obtain the following ratio:

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

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. The name of the ratio, *InetSpe*, was chosen to show that this ratio is a variant of the INET model for short-term trading used here for speculation purposes. This ratio is often used for trading purposes. We remark that in Chris Burniske's original model for annual data, 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:

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

where μ is the mean value of the InetSpe ratio computed over a specific period of time b, σ is the standard deviation over the same period b, and a is the time sample used to compute the moving average.

3.6. Volt Valuation Model

Ref. [56] 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 (VOLT is the name of Evans' fictitious token). They assumes that a player in the economy will spend all their annual income during a specific year and that the player has two choices: either hold their money in cash, or save their 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 substantial 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 by

$$NVVolt = \frac{Network\ Value}{M_{Volt}} \tag{14}$$

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

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

where μ is the mean value of the $NVVolt$ ratio computed over a specific period of time b, σ is the standard deviation over the same period b, and 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:

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

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 computed 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 [47,48,57], 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. 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. While these two thresholds could have been optimized, 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.

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. To test 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.

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, Ref. [9] 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-coin 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 [58] 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, and 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 a period of 90 days to compute the moving averages and 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 but are 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, accessed on 1 July 2022, 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. The metrics we employed are briefly discussed below in Table 1.

Table 1. Evaluation metric acronyms and meanings.

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

4. Results

4.1. Data

We used daily Bitcoin data (BTC) from 17 August 2011 to 30 March 2022 obtained from Glassnode; the download links are reported in 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.

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

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

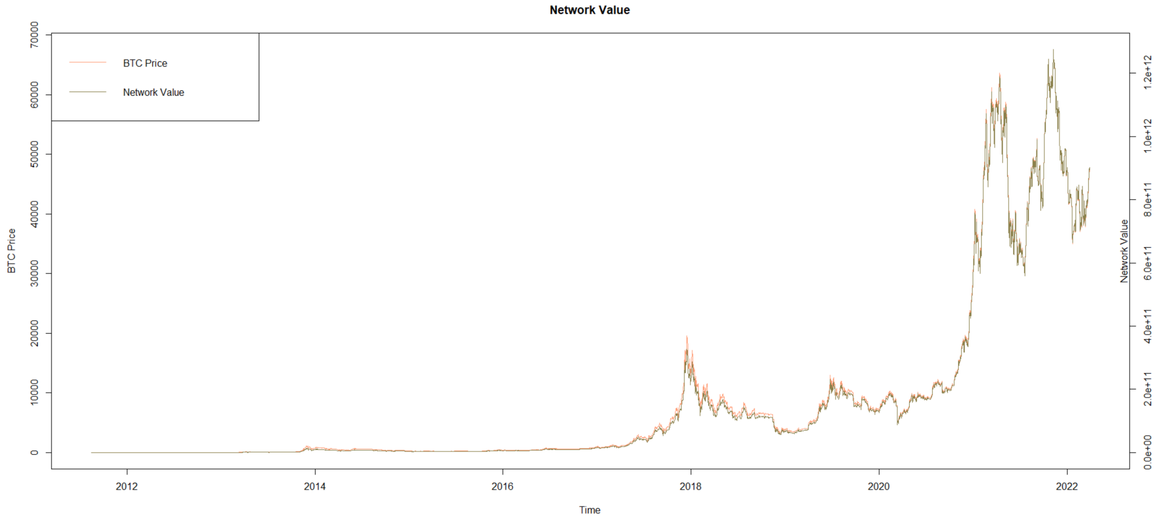

Figure 1. Bitcoin price and network value.

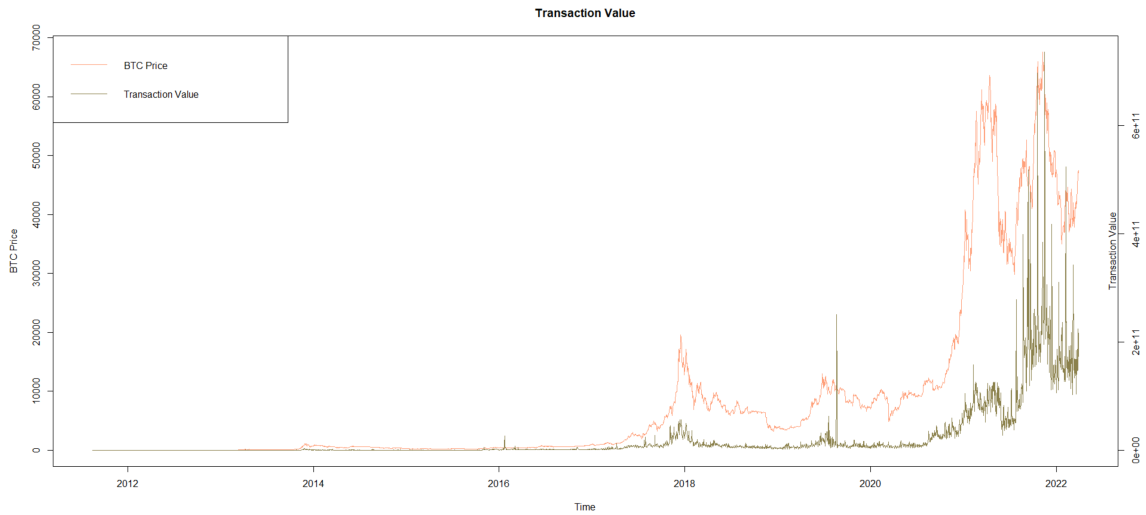

Figure 2. Bitcoin price and daily transaction value.

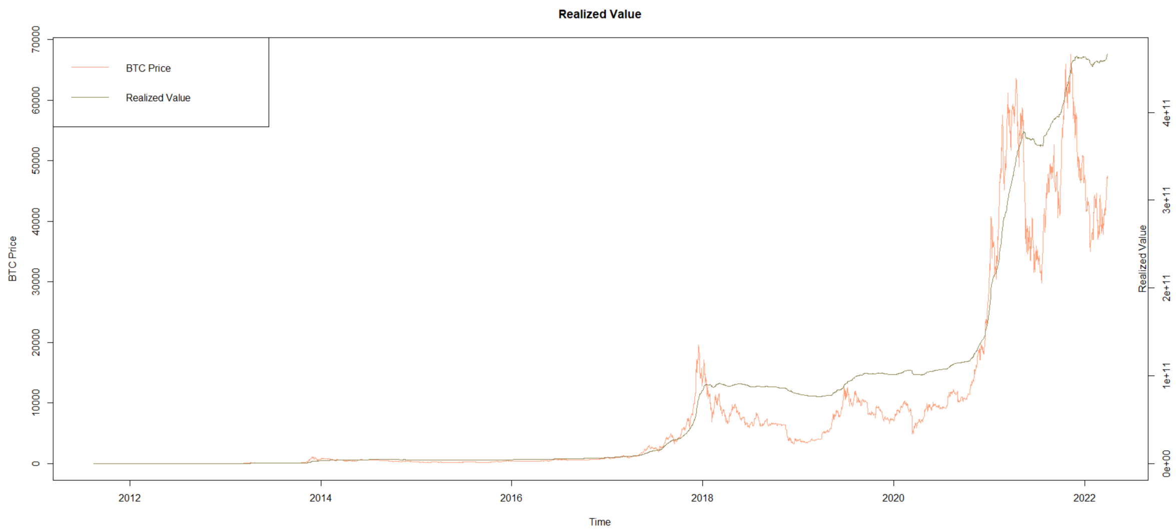

Figure 3. Bitcoin price and realized value.

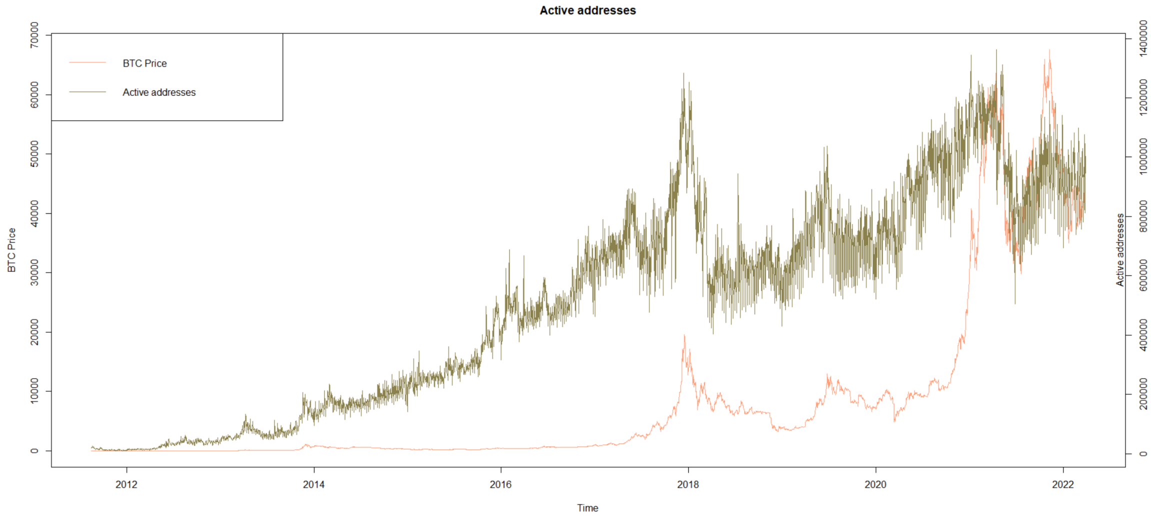

Figure 4. Bitcoin price and active addresses.

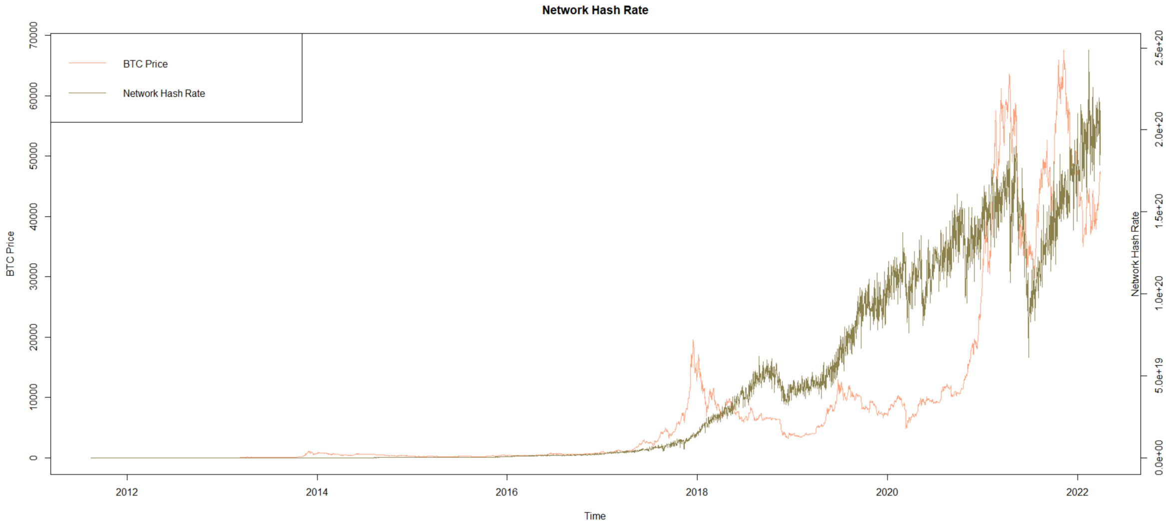

Figure 5. Bitcoin price and network hashrate.

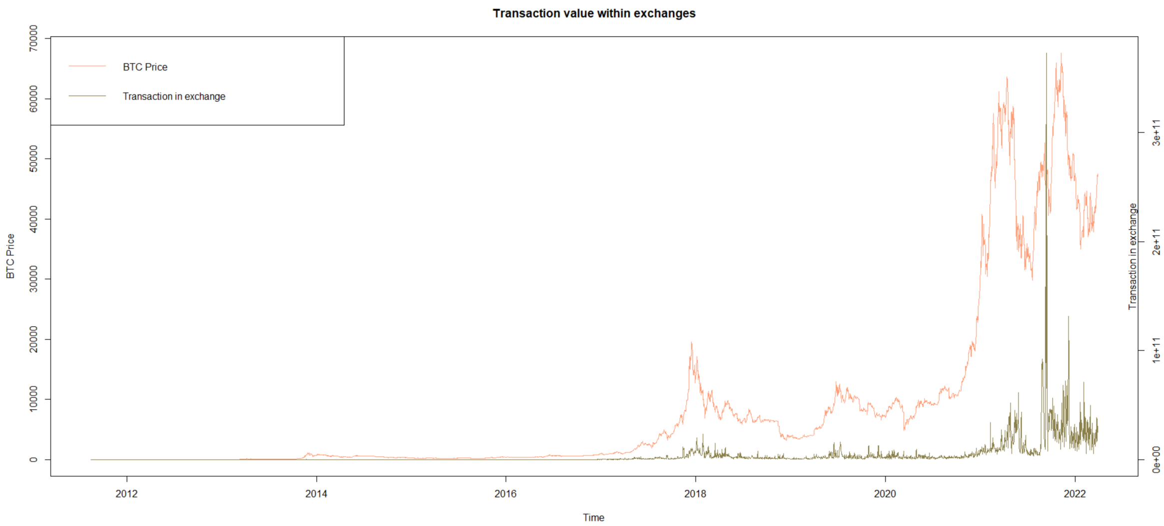

Figure 6. Bitcoin price and daily transactions value within exchanges.

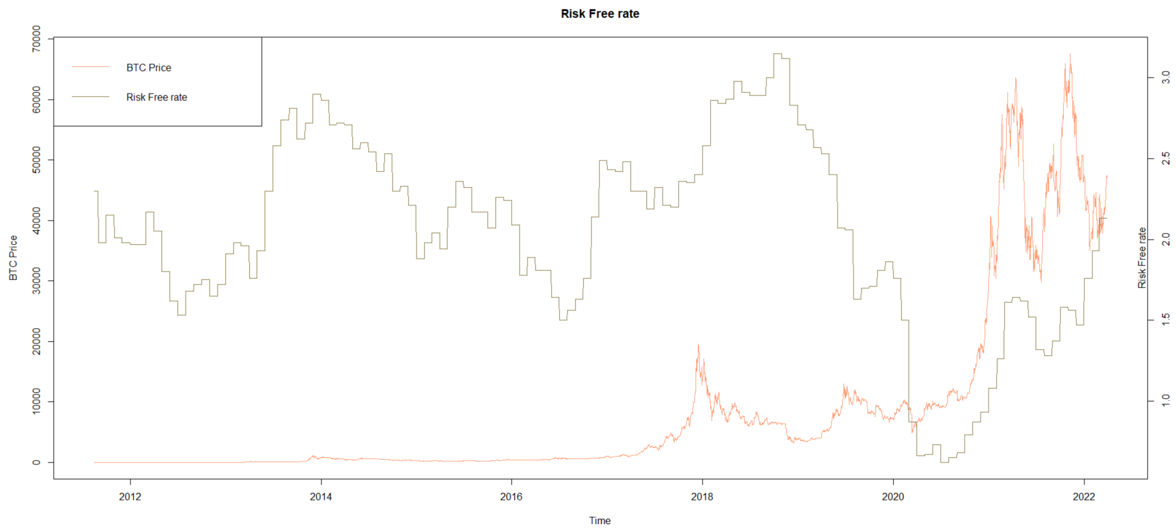

Figure 7. Bitcoin price and risk-free rate.

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.

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.

	BTC (Price)	*BTC (Log Returns)*	*NVTS_Z*	*NVRV_Z*	*NVHRS_Z*	*NVMLS_Z*	*NVOLS_Z*	*INETSPE_Z*	*VOLT*
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	67,589.01	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	104,600	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.

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 are 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, as well the tests for the equality to zero of each Sharpe ratio for non-independent and identically distributed elliptical returns; see [59] (chapter 3) for more details. Table 4 also reports the test by [60] for the equality of all Sharpe ratios, which holds under the general assumption that the excess returns are stationary and ergodic.

Table 4. Selected evaluation metrics for all trading strategies.

Strategy	*Net.Trading.PL*	*Max.Drawdown*	*Max.Equity*	*Min.Equity*	*Ann.Sharpe*	*Profit.To. Max.Drawdown*	*Num.Txns*
NVTS	86,002	−97,656	147,472	−1126	0.31	0.88	38
NVRV	46,685	−35,065	61,577	−574	0.41 *	1.33	15
NVHR	37,728	−55,538	47,901	−7636	0.20	0.68	17
NVML	43,439	−18,847	50,224	−2739	0.47 *	2.3	20
NVOL	45,589	−41,460	53,747	−2877	0.30	1.1	18
INET	49,862	−16,249	58,375	0	0.55 **	3.07	104
VOLT	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 10% probability level; ** Significantly different from zero at the 5% probability level.

Figures A1–A7 in Appendix B report 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 implied that all previously bought Bitcoins must be sold at that time.

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, its performance could likely be improved using a profit-taking strategy. Given that this goes beyond the scope of this work, we leave it as an avenue for further work.

Another interesting strategy uses the network-value–Metcalfe's law (*NVML*) ratio, 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–max-drawdown, equal to 2.3. The strategy using the network-value–Odlyzko's law (*NVOL*) ratio has performance metrics that are rather similar to the strategy using the network-value–Metcalfe's law ratio, even though they are generally slight worse than the latter. Moreover, the max drawdown and the profit–max-drawdown ratio (1.10) are much worse than the approach that uses Metcalfe's law.

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

The network-value–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 for further work.

On the other side of the spectrum, the VOLT model had the worst performance measures in almost all cases: interestingly, this model also experienced 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, and the highest profit–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 makes this trading strategy one of the most interesting considered so far. However, despite all these differences, we note that the test by [60] 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 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 result 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 has been known since the work by [37] that blockchain networks can be fairly well modeled by it, as it 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 for identifying 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 [61–64]. Moreover, there is also a debate on whether the introduction of Bitcoin futures in December 2017 crashed the market prices; see [12,65–70]. 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 9 December 2017 in the first sample, and on 30 March 2022 in the second sample).

Table 5. Selected comparison of trading strategies: **17 August 2011/9 December 2017**.

Strategy	*Net.Trading.PL*	*Max.Drawdown*	*Max.Equity*	*Min.Equity*	*Ann.Sharpe*	*Profit.To. Max.Drawdown*	*Num.Txns*
NVTS	14,412	−5070	14,748	−1139	0.97 **	2.84	20
NVRV	10,575	2078	12,653	−539	0.87 **	5.08	5
NVHR	4928	−1247	5334	−309	0.99 **	3.94	11
NVML	1348	−855	2195	−171	0.52 *	1.57	8
NVOL	1078	−719	1755	−512	0.40	1.49	9
INET	8798	−2078	10,876	0	0.72 **	4.23	63
VOLT	−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 10% probability level; ** Significantly different from zero at the 5% probability level.

Table 6. Selected comparison of trading strategies: **10 December 2017/30 March 2022**.

Strategy	*Net.Trading.PL*	*Max.Drawdown*	*Max.Equity*	*Min.Equity*	*Ann.Sharpe*	*Profit.To. Max.Drawdown*	*Num.Txns*
NVTS	32,014	−36,974	33,052	−6059	0.47	0.87	12
NVRV	32,119	−32,552	52,609	−2009	0.53	0.98	6
NVHR	27,986	−48,321	52,183	−1360	0.35	0.58	7
NVML	60,025	−22,965	64,808	−6758	0.77 *	2.61	11
NVOL	67,803	−65,104	99,413	−6675	0.51	1.04	10
INET	25,554	−18,611	28,727	−4749	0.50	1.37	58
VOLT	35,319	−97,656	87,840	−11,490	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 10% probability level.

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–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 [65,68,71] 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.

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

Strategy	*Net.Trading.PL*	*Max.Drawdown*	*Max.Equity*	*Min.Equity*	*Ann.Sharpe*	*Profit.To. Max.Drawdown*	*Num.Txns*
NVTS	90,167	−84,680	131,147	−1825	0.36	1.06	51
NVRV	56,476	−78,834	94,966	−2749	0.24	0.72	20
NVHR	58,045	−17,061	58,434	−7471	0.59 **	3.40	26
NVML	64,323	−26,204	65,491	−2788	0.45 *	2.45	24
NVOL	65,536	−80,873	104,576	−7520	0.29	0.81	24
INET	38,272	−18,715	49,711	−1415	0.39 **	2.04	238
VOLT	8171	−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 10% probability level; ** Significantly different from zero at the 5% probability level.

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; 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-asset 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 trend in the financial literature that shows 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–max-drawdown, thus showing it 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–max-drawdown were much worse and, in general, its metrics worsened after 2017.

A variant of the Chris Burniske's [55] INET model 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 for generating long signals, but bad for 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 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 (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, see https://quoteinvestigator.com/2011/08/09/remain-solvent, accessed on 1 July 2022 for more details).

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 continued to slowly increase over time, despite improvements in mining equipment energy efficiency and a 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, accessed on 1 July 2022). This apparent contradiction is due to the continuous increase in the Bitcoin hashrate (see www.blockchain.com/explorer/charts/hash-rate, accessed on 1 July 2022), 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*" (see https://insights.glassnode.com/the-week-onchain-week-40-2022, accessed on 1 July 2022). Ref. [72] 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 also highlight 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. As 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 for 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, accessed on 1 July 2022). 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 here. Moreover, we did not consider transaction fees and short sales. Even though there is a trend towards 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 suggests that an analysis using approaches based on social network analysis would be a natural extension for understanding the ultimate reasons behind the phenomena reported in this work. We leave this issue as an interesting avenue for further research.

Author Contributions: Conceptualization, Z.Y. and D.F.; methodology, Z.Y. and D.F; software, Z.Y. and D.F; validation, Z.Y. and D.F.; formal analysis, D.F.; investigation, Z.Y. and D.F.; data curation, Z.Y. and D.F.; writing—original draft preparation, Z.Y.; writing—review and editing, D.F.; visualization, Z.Y. and D.F.; supervision, Z.Y. and D.F.; project administration, Z.Y. and D.F.; funding acquisition, D.F. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Data Sources

(1) *Price data*: this is free data; the source is as follows: https://studio.glassnode.com/metrics?a=BTC&category=&m=market.PriceUsdClose, accessed on 1 July 2022.
(2) *Network value*: this is free data; the source is as follows: https://studio.glassnode.com/metrics?a=BTC&category=&m=market.MarketcapUsd, accessed on 1 July 2022.
(3) Realized value: this is not free data; the source is as follows: https://studio.glassnode.com/metrics?a=BTC&category=&m=market.MarketcapRealizedUsd, accessed on 1 July 2022.
(4) Active addresses: this is free data; the source is as follows: https://studio.glassnode.com/metrics?a=BTC&category=&m=addresses.ActiveCount, accessed on 1 July 2022.
(5) Network hashrate: this is free data; the source is as follows: https://studio.glassnode.com/metrics?a=BTC&category=&m=mining.HashRateMean, accessed on 1 July 2022.
(6) Transaction in exchange: this is not free data; the source is as follows: https://studio.glassnode.com/metrics?a=BTC&category=&m=transactions.TransfersVolumeWithinExchangesSum, accessed on 1 July 2022.
(7) Risk-free rate: this is free data; the source is as follows: https://fred.stlouisfed.org/series/GS10, accessed on 1 July 2022.

Appendix B. Trading Strategies Performances

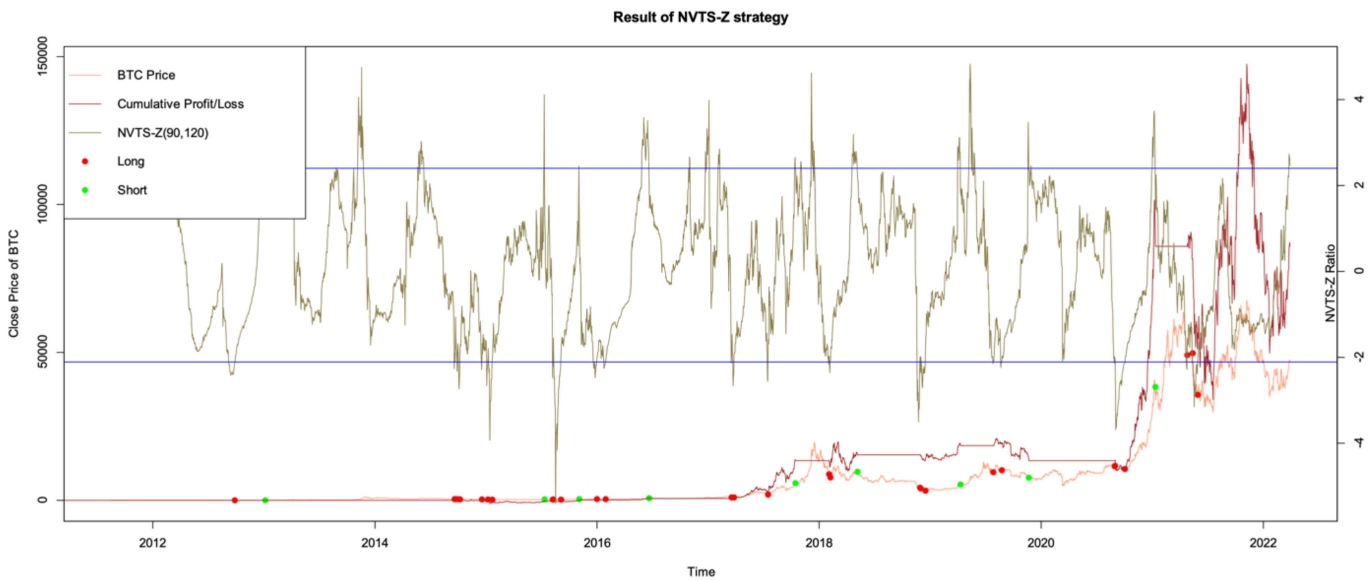

Figure A1. *NVTS-Z* strategy: BTC price (orange line, left-hand side), cumulative profit/loss (red line, left-hand side), *NVTS*-Z ratio (brown line, right-hand side), long and short thresholds (blue lines, right-hand side), long orders (red points), and short orders (green points).

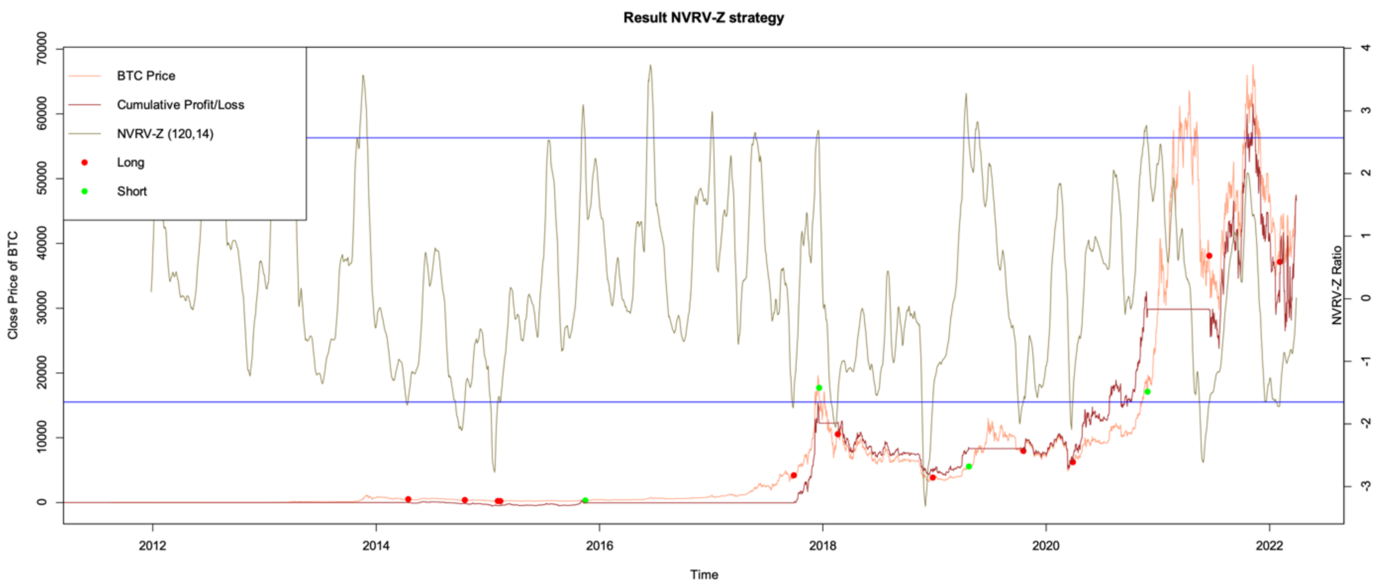

Figure A2. *NVRV-Z* strategy: BTC price (orange line, left-hand side), cumulative profit/loss (red line, left-hand side), *NVRV*-Z ratio (brown line, right-hand side), long and short thresholds (blue lines, right-hand side), long orders (red points) and short orders (green points).

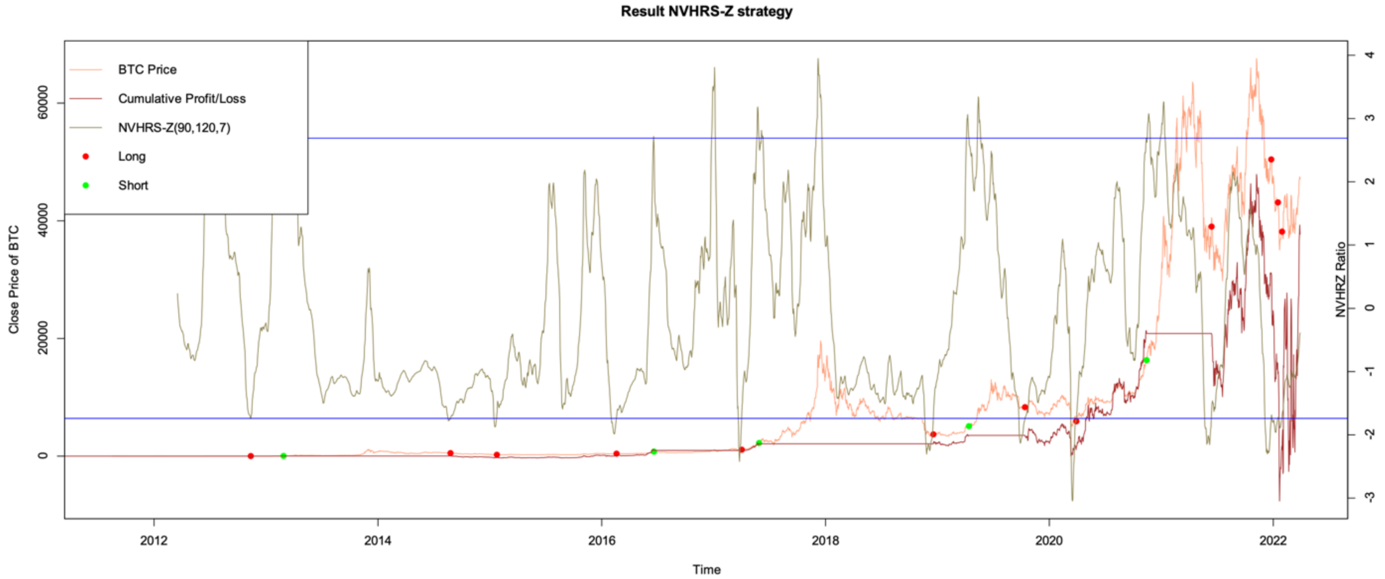

Figure A3. *NVHRS-Z* strategy: BTC price (orange line, left-hand side), cumulative profit/loss (red line, left-hand side), *NVHRS*-Z ratio (brown line, right-hand side), long and short thresholds (blue lines, right-hand side), long orders (red points), and short orders (green points).

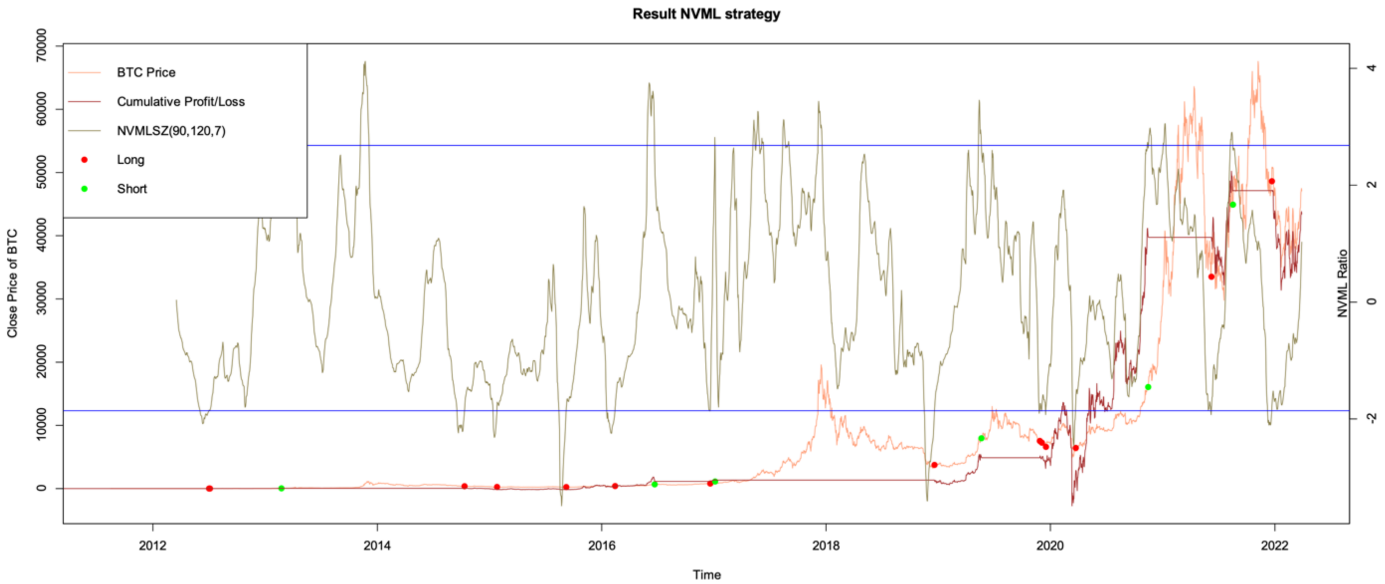

Figure A4. *NVMLS-Z* strategy: BTC price (orange line, left-hand side), cumulative profit/loss (red line, left-hand side), *NVMLS*-Z ratio (brown line, right-hand side), long and short thresholds (blue lines, right-hand side), long orders (red points), and short orders (green points).

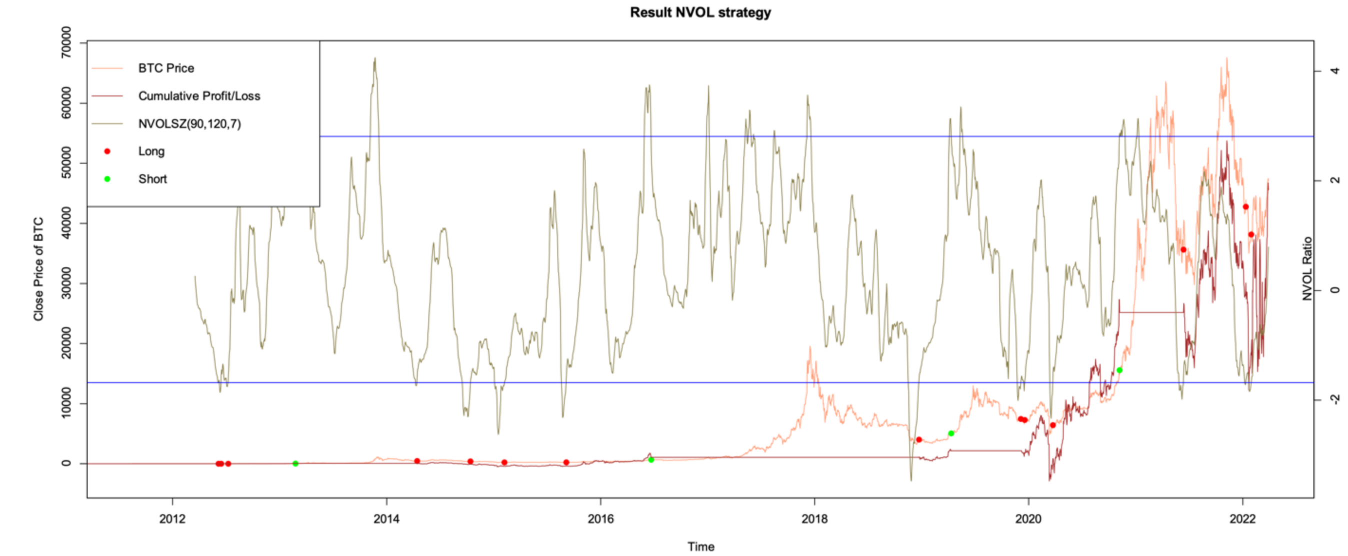

Figure A5. *NVOLS-Z* strategy: BTC price (orange line, left-hand side), cumulative profit/loss (red line, left-hand side), *NVOLS*-Z ratio (brown line, right-hand side), long and short thresholds (blue lines, right-hand side), long orders (red points), and short orders (green points).

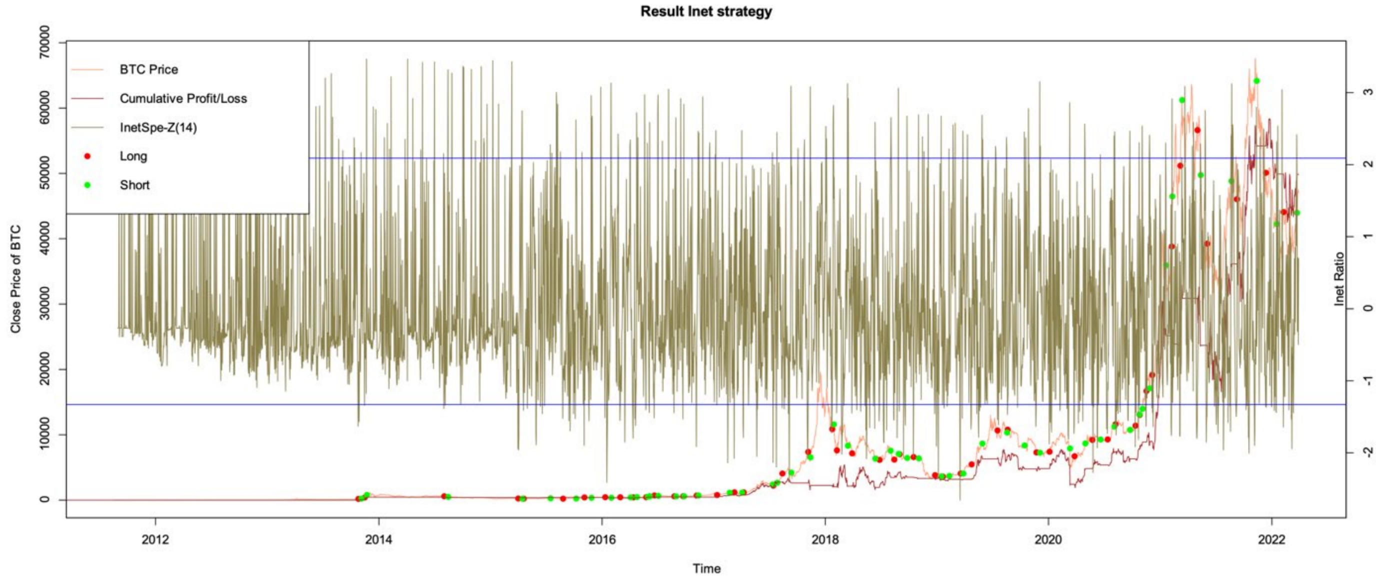

Figure A6. *InetSpe-Z* strategy: BTC price (orange line, left-hand side), cumulative profit/loss (red line, left-hand side), InetSpe-Z ratio (brown line, right-hand side), long and short thresholds (blue lines, right-hand side), long orders (red points), and short orders (green points).

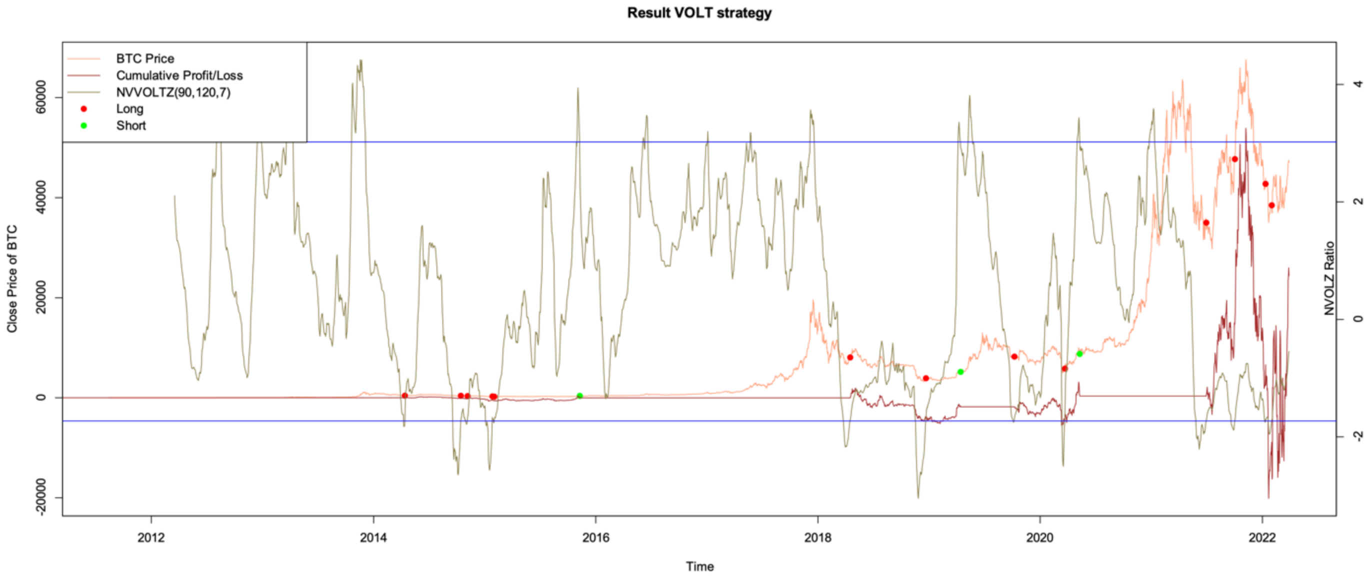

Figure A7. *VOLT* strategy: BTC price (orange line, left-hand side), cumulative profit/loss (red line, left-hand side), VOLT ratio (brown line, right-hand side), long and short thresholds (blue lines, right-hand side), long orders (red points), and short orders (green points).

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