Bitcoin Network Demand Model (BYTE3)

May 2020

Contents

► Section 1: Introduction

The aim of this paper is to provide readers with a brief introduction to Bitcoin (BTC), the World's largest digital asset by market capitalisation[1], and the importance of the "Network Effect" as a key determinant of its value. The latter is a central concept in economics whereby the value of a good or service increases when more users join a given network. Classical examples of the network effect can be observed in widely used gadgets and services such as the Telephone, Email and Internet and more recently in Social Media platforms such as Facebook and Twitter.

Having established the importance of the network effect in influencing the value of BTC, this paper goes on to show how it can be quantified and exploited using a set of key indicators which aim to measure the level of demand over the Bitcoin Network (as a proxy for the network effect). A more practical application of these indicators is further investigated by showing how they can be used as part of a simple rules-based ensemble (composite) trading strategy with the aim of delivering better risk-adjusted returns and lower drawdowns than a passive holding of BTC.

This paper comes at a key time in the development of the digital asset industry. As bitcoin and digital assets become more widely accepted by the investment community, there is an increasing requirement for service providers to reduce operational risk from investments. With increasing demand from corporate investors, the investment landscape has evolved significantly in the last two years, now offering investors services such as insured custody, prime brokerages and order management systems.

With the operational risks around digital assets largely resolved, investors are looking for improved sources of data on digital assets to mitigate price risks faced in the market. Corporate interest is growing, with $0.5bn new capital invested in digital assets in Q1 2020[2] through one US investment manager, Grayscale (GBTC).

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[1] https://www.cryptocompare.com/ , as of 8th May, 2020
[2] https://grayscale.co/insights/grayscale-q1-2020-digital-asset-investment-report/

We believe this report is primarily likely to appeal to investors, traders, the buy-side research community and index providers.

► Section 2: Context

2.1 Bitcoin as Digital Value

The Bitcoin Network is a decentralized and distributed ledger hosted by over 10,031 nodes across more than 100 countries[3]. BTC, the native currency of the Bitcoin Network, is a deflationary digital asset that has a finite supply of 21 million coins. To the present day[4], 18.4 million BTC have been minted (mined) and approximately 2.7 million of these are inaccessible due to lost access keys (Chainalysis, 2018). New BTC can only be minted through committing hash-based proof of work computing power, generated through a Graphics Processing Unit (GPU) or Application Specific Integrated Circuit (ASIC). The rate at which new BTC can be minted is controlled by the network's algorithmic programming, releasing new BTC approximately every 10 minutes. The BTC for that period are awarded to the entity controlling the computer power, or miner, that successfully solves a mathematical proof. In short, every 10 minutes a new mathematical proof is solved.

The limited issuance of BTC has led some to label it as "digital gold". While this is not entirely unfounded, the supply constraint alone does not justify the label of digital gold. In order to be recognised as digital gold, we firmly believe that there must also be an established base-level of demand for the asset that supports a minimum price level. It is the relative relationship between the supply and demand for this asset which supports its value.

At this point, it is necessary to make a clear distinction between bitcoin (BTC), the digital asset, and the Bitcoin Network – the infrastructure that enables the transfer of BTC. While they are interdependent, they serve different purposes. The Bitcoin Network is a global public *exchange*

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[3] Reported by https://bitnodes.io/ as of 8th May, 2020
[4] As at 1st May 2020

infrastructure while BTC is the *medium of exchange* required for using the Bitcoin Network. Since BTC is required for using the Bitcoin Network, we can evaluate the utility or value of BTC through measuring and calculating the utility of the Bitcoin Network that it operates on.

Metrics for measuring the utility of the Bitcoin Network can be split into two groups: those around *users* and those around *network demand*. This paper will reference work done around modelling the utility of the network based on users, before presenting a novel approach that focuses on utility based on network demand. Network demand, in the context of this paper, refers to on-chain transaction volume, the velocity of the network, the changing levels of inventories and the total fees paid to miners.

Examples of value exchange across the Bitcoin Network include international payment router Bitpesa and payment processor Bitpay. Bitpesa utilizes the Bitcoin network to circumvent the costly and often slow process of international settlements[5]. Another prominent user of the Bitcoin network for international settlements is Bitpay, who claim to have facilitated close to $1bn of payments in 2017[6]. Similar to Bitpesa, Bitpay is a regulated company that only facilitates legitimate, legal and therefore taxable payments.

2.2 Bitcoin and the "Network Effect"

As a peer-to-peer distributed network, BTC benefits from *network effects* - the positive relationship between the size of the user base, or activity, on the network. The more vibrant the network, the greater the value.

The network effect, or Metcalfe's Law (Metcalfe, 1995), was first modelled by Robert Metcalfe as $v = n^2$, where *v*, in this equation, represents the value of the network and *n* refers to the number of users. A graphical representation of this law is shown in Figure 1 and compared with the value of a network where only a linear relationship exists between v and n. A number of variations on

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[5] https://www.leadersleague.com/en/news/elizabeth-rossiello-bitpesa-we-have-lowered-the-cost-of-international-payments-by-75

[6] https://bitpay.com/blog/bitpay-growth-2017/

the relationship between v and n have been proposed. We have modelled a number of variations to identify the most relevant relationship for BTC's specific use case, settling on Zipf's law (Zipf, 1949), which states $v = n^{1.5}$.

The network effect demonstrates a positive correlation between network usage and network value. This paper builds on this idea by attempting to measure Bitcoin network activity in place of the number of connected active users .

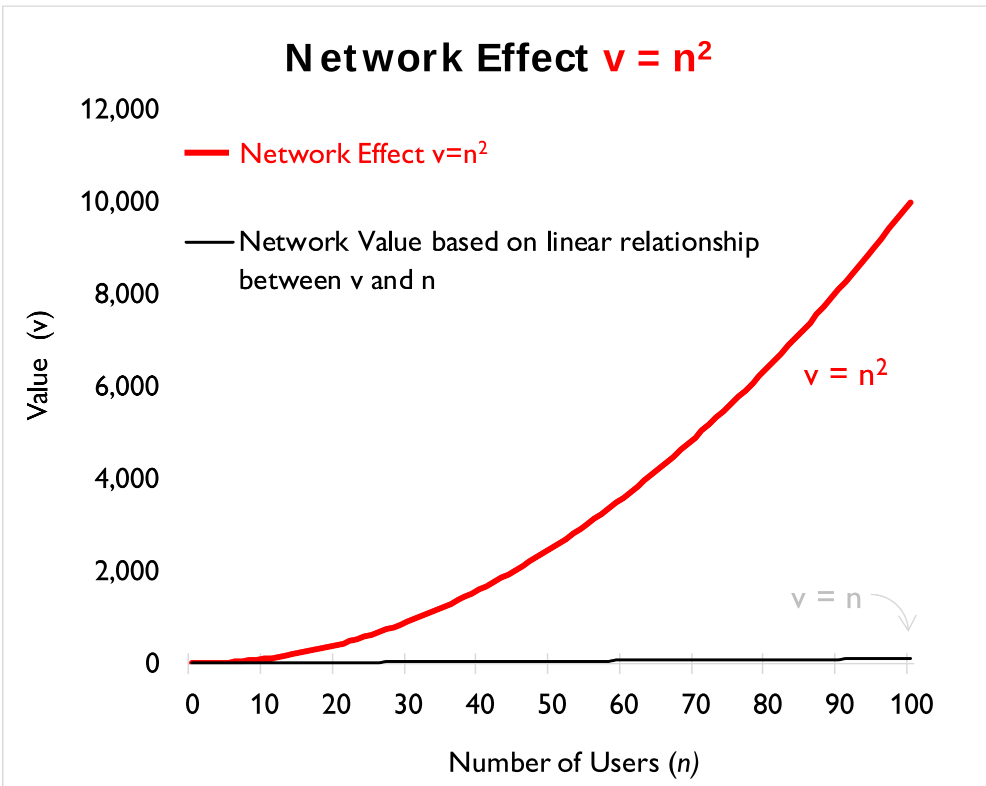

Figure 1: Illustrating how the value of a Network increases with the square of the number of users ("network effect") as modelled by Robert Metcalfe.

2.3 Moving Average Trading Strategies

Moving Averages (MA) are one of the oldest and most widely used techniques in technical analysis for trend detection (Zakamulin, 2018). They work by filtering signal from noise in a timeseries (Miccolis & Goodman, 2012) and are calculated by rolling a window of fixed-sized recursively across a timeseries and averaging the values in the window during each recursion. Each time the window is rolled, a new data point is added and the last one removed (Zakamulin, 2018). Simple Moving Averages are the most commonly used MAs and are calculated by equally weighting data points in the MA calculation window (Zakamulin, 2018).

Miccolis & Goodman (2012) note that MAs cannot predict turning points in a timeseries, but they can identify trends promptly as they develop. As a result, they are useful for positioning "portfolios in light of current market conditions" (Zimmerer & Carrington, 2016). Zakamulin (2018) notes that there exist a number of trading rules used to generate signals using MAs including momentum rule, price-minus-moving-average (PMMA), change of direction rule and double crossover amongst others.

When using MAs, a key consideration is the length of the window ("lookback" period) to use (Zakamulin, 2018; Miccolis and Goodman, 2012). Short lookback periods respond faster, but are also prone to higher whipsaw (false-signals). Conversely, longer lookback periods result in more stable filters, but at the cost of being less timely (Miccolis & Goodman, 2012). One key advantage of double-MA crossovers, which employs two moving averages – one shorter more responsive averaging period and one longer more stable averaging period – is that they can help reduce many false signals associated with techniques such as the PMMA rule whilst remaining responsive (Zakamulin, 2018).

2.4 Ensemble Methods

In machine learning and statistics, ensemble methods combine multiple learning algorithms[7] to achieve better predictive performance than can be achieved by any of the individual learners (Seni & Elder, 2010). In a practical sense, ensemble strategies can be thought of as a "committee of experts" whose combined (weighted) predictions[8] are used to reach a conclusion. Ensemble methods are widely used to improve the generalizability[9]of a model and reduce the risk of

[7] In the context of this paper a *learning algorithm* is a trading algorithm.

[8] There are different ways to combine the predictions of the committee e.g. majority voting, veto voting, etc.

[9] A *generalizable model* is one which can be applied to a wide variety of scenarios as opposed to a few specific scenarios.

overfitting, with real world applications in investment timing, drug discovery, fraud detection and recommendation systems (Seni & Elder, 2010).

When using Ensemble methods, one of the key considerations is how to combine the decisions of the individual learners (Alpaydin, 2009). Whilst a number of techniques exist to do this, one of the simplest approaches is to take a *linear combination* of the classifiers using *equal weights* (Alpaydin, 2009, pp. 424-425). Zhou (2012, p. 69) notes that "owing to its simplicity and effectiveness, simple averaging is among the most popularly used methods and represents the first choice in many real applications".

Alpaydin (2009) notes that *diversity* is a key component of building successful ensembles – as it ensures that the classifiers make different errors on new data instances. Commonly used ways to achieve diversity amongst the learners is by using different algorithms, input representations and training datasets amongst other techniques (Alpaydin, 2009, pp. 420-422).

► Section 3: Methodology

3.1 Introduction

ByteTree has constructed a series of metrics (Bitcoin Network Demand Set "BYTE") to measure Bitcoin Network Demand using data extracted from the cryptocurrency network. Using these metrics, ByteTree aims to determine when the price of BTC is overvalued and when it is trading at a discount to fair value. The goal is to incorporate this information into a composite BTC trading strategy in order to help investors and traders improve overall risk-adjusted returns and protect against the risk of large drawdowns when trading or investing in BTC. The schematic below (Figure 2) summaries the key steps involved in this process and are expounded in Sections 3.2 – 3.5 that follow.

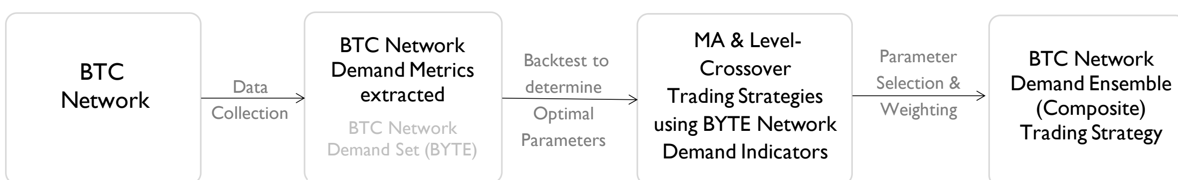

Figure 2: Process flow chart showing how the Bitcoin Network effect is extracted using a series of network demand metrics and incorporated into a composite BTC Trading strategy that aims to improve risk-adjusted returns and protect investors against the risk of large drawdowns

3.2 Data Collection

ByteTree is a blockchain data provider that captures, enriches and computes a rich set of high-quality, real-time, raw (as well as augmented) blockchain data. The data collection and processing architecture involves four core steps explained below.

3.2.1 Capture

The first step involves data capture carried out over three distinct layers with the aim of capturing raw data for each crypto-asset. The first layer connects to the node to stream incoming block-level data, the second layer captures price and exchange data at the ticker level whilst the third layer collects unseen data from alternate blockchain forks.

3.2.2 Conform

The second step involves keeping track of relative time in the system and to do this, the Volume Weighted Average Price (VWAP) for each network is calculated and the USD price reference per tick is broadcast (Post-VWAP). As network supply and market capitalization information is necessary for this calculation, this is also captured and used to layer together the different sources of information with matching time stamps. The initial snapshot of the data at time *t* is generated and stored.

3.2.3 Compute

In this stage, the data generated from the output of the conformer stage is munged. This step is triggered after the conformer snapshot. It involves defined data transformation tasks such as trend (moving average) calculations, cumulation, ratio computation, indexation and inflation in a hierarchical sequence. This stage captures the addition of wallets and entity analysis, as well any flagged transaction identification alerts.

3.2.4 Service

In the final stage, data is comprehensively streamed to the client's user interface, Remote Procedure Calls (RPC) and Application Programmers Interface (API) as accessible endpoints to external clients. All the data captured in stage 3.2.1 and computed in stage 3.2.3 is provided through these endpoints. The data is optimized for streaming performance and administered (permissioned) through a token system which acts as a proxy for all upstream events that require propagation to UI.

3.3 ByteTree Network Demand Indicators

ByteTree's Bitcoin Network Demand set of Indicators ("BYTE") measures Bitcoin Network demand as a proxy for the Bitcoin Network effect. The data is extracted from the Bitcoin Network as outlined in Section 3.2 and a brief explanation of each indicator[10] and how it relates to Bitcoin Network demand is outlined below and a summary is provided in Table 1.

3.3.1 Fees

BTC Fees represent the *cost of sending a transaction over a network*. They are paid to miners to facilitate transactions in the Bitcoin Network and process their transactions as soon as possible (Morris, 2020a). Fees tend to be a fixed amount regardless of the transaction size; thus large transactions tend to be cheap whilst micropayments are comparatively expensive. The level of fees is an indicator of the level of economic activity within the Bitcoin Network. Rising Fees are an indicator of growing network demand whilst falling Fees indicate the opposite. When using Fees as an indicator of network demand, we use weeks rather than days due to the weekday bias[11].

3.3.2 Transaction Value

The Transaction Value measures the on-chain transaction value in BTC or US dollars, adjusted for change outputs (Bennett, 2019). It indicates the *value of economic exchange* between two

[10] It is worth nothing that ByteTree computes other metrics to measure network demand including *General Spend*, *Network Value to Transaction Ratio* and *Transactions*. However the indicators mentioned in Section 3.3 are the ones ByteTree has found to be the most useful for measuring network demand based on preliminary work done in this area. If you wish to know more about the other indicators please contact us here.

[11] The Weekday bias is the basis for the default timeframe used by ByteTree. This is because a week is the minimum economic cycle in crypto networks and adjusts the data for less active weekends. Mondays to Fridays are routinely the busiest days whereas weekends see a significant drop in traffic. By measuring the BYTE Indicators across the rolling week, we get the most up to date week-on-week comparisons. Further information on the Weekday bias can be found here.

parties over the Bitcoin Network and is calculated in individual blocks of weeks rather than days – owing to the Weekday bias. By way of analogy, the Transaction Value is to a crypto analyst what sales or revenue is to an equity analyst. Calculating the Transaction Value is complicated and involves two components: a transaction amount and a change output. To identify the economic value of a transaction we have to identify and subtract the change output from the transaction value.

3.3.3 Velocity

Network Velocity, as the name suggests, indicates the *speed at which coins move* around the Bitcoin Network measured on a weekly basis. It is a non-price based indicator calculated by dividing the Transaction Value (measured in coins) by the Total Coin Supply and then annualizing this figure[12]. A higher (lower) velocity indicates that each active coin moves through the network more (less) times in a year. For example, when BTC has a velocity of 1000%, it means an average BTC is circulating 10 times per year[13]. Velocity serves as a sentiment indicator with the level of velocity more important than the direction of velocity (Morris, 2019a). Very high readings are indicative of investor hype (frequently a sell signal) and lower readings are indicative of investor despair (frequently a buy signal) relative to current market conditions (Morris, 2019b).

3.3.4 Miner's Rolling Inventory

The Miner's Rolling Inventory (MRI) is a metric which quantifies the *change in BTC inventory level* held by miners and serves as another proxy for the change in Bitcoin Network value. It is calculated as the change in BTC first spend[14] (calculated over a given number of weeks) divided by the change in BTC generated over the same period and multiplied by 100. For example, if

[12] Multiplying by 52 when working with Weekly data

[13] As velocity is an average network measure, other coins may be circulating more or less than this amount.

[14] Whenever a miner solves a block, the newly minted bitcoins that have never been spent show up on ByteTree as unspent inventory ("inventory"). When they are first spent, they become *first spend* and every time they are spent thereafter they become *general spend* or *transaction value* (Morris, 2020b).

miners generated 76,900 BTC while first spend saw 78,300 BTC join the network, the MRI would be 1.8% suggesting these many more BTC have been "spent" than mined.

An MRI above 100% means that miners are selling more than they mine and running down inventory, whereas an MRI below 100% means that miners are hoarding bitcoins (Morris, 2020b). A high MRI is reflective of a strong market bid that the miners are comfortable selling into. When that bid fades, the miners hold back, and as a result inventories rise and MRI falls.

Indicator	Measures	Interpretation
Fees	Cost of sending a transaction over a network	↑ Fees = ↑ Network Demand ↓ Fees = ↓ Network Demand
Transaction Value	Value of economic exchange between two parties over the Bitcoin Network	↑ Transaction Value = ↑ Network Demand ↓ Transaction Value = ↓ Network Demand
Velocity	Speed at which coins move around the Bitcoin Network	High Velocity = High Network Demand Low Velocity = Low Network Demand
Miner's Rolling Inventory	Change in BTC inventory level held by miners	High MRI = High Network Demand Low MRI = Low Network Demand

Table 1: Summary of ByteTree's Bitcoin Network Demand Set of Indicators which aim to measure Bitcoin Network demand and their interpretation.

3.4 Signal Generation

3.4.1 MA and Level Crossover

To generate BTC trading signals exploiting the Bitcoin Network Demand Set of Indicators (Section 3.3), a double-MA crossover trading strategy is utilized for indicators 3.3.1 and 3.3.2 and a level-crossover trading strategy is adopted for Indicators 3.3.3 and 3.3.4. In the former case, the trend direction is considered a better indicator of network demand than the level whereas in the latter case the opposite is true. Figure 2 clarifies how these signals are generated for each indicator based on a long-only trading strategy.

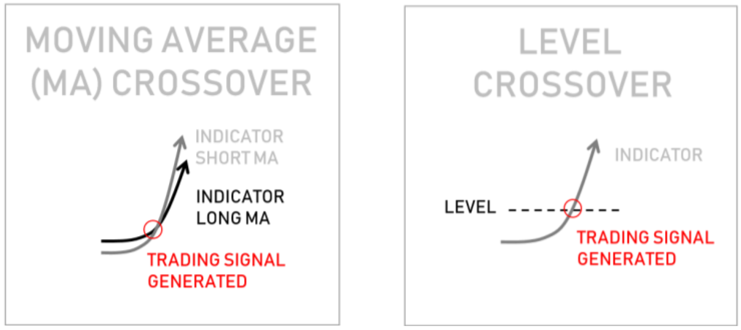

Figure 3: Illustrating how a MA-crossover and level-crossover trading signal is generated for a long-only trading strategy based on the Bitcoin Network demand set of Indicators

3.4.2 Parameter Optimisation

Having identified the signal generation strategy for each of the four indicators, a range of parameters is tested, for each indicator, to identify the "optimal" ones to use when trading BTC. For indicators 3.3.1 and 3.3.2, a range of short and long MA lookback periods are tested (based on the considerations outlined in Section 2.3) as part of a BTC long-only trading strategy, whereas different threshold levels are tested for indicators 3.3.3 and 3.3.4. The complete range of parameters tested are outlined in Table 2 below.

Indicator	Range of Parameters Tested		
	Short MA lookback period	Long MA lookback period	Level (Threshold) Crossover
Fees	[1,52]; Step size = 1	[1,52]; Step size = 1	-
Transaction Value	[1,30]; Step size = 1	[1,30]; Step size = 1	
Velocity	-	-	[350,1450] ; Step size = 50
Miner's Rolling Inventory			[95,105] ; Step size = 1

Table 2: Range of parameters tested to establish the optimal short and long term MA lookback period and thresholds when trading BTC long-only using the network demand indicators listed above.

The optimization was conducted over the period 1st July 2014 - 13th January 2020. Whilst this is a relatively short test period, it was specifically chosen to reflect the time during which BTC has been trading as a more-mature crypto currency. For each indicator and relevant parameter combination (Table 2), five performance metrics were calculated: *Compound Annual Growth Rate*, *Standard Deviation*, *Sharpe Ratio*, *Maximum Drawdown* and the *Number of Trades*. A brief explanation of the statistics is provided in Section 8.1. The results were plotted as heatmaps and scatterplots and used to select the optimal parameter set for each network demand indicator. To avoid the risk of overfitting and look-ahead bias, the optimal parameters selected for each indicator are not the ones that result in the best overall performance but rather the ones that occur in a zone of stable performance – as identified using the heatmaps and scatterplots. An example of this is shown for Fees statistics is in Section 8.2.

3.5 Bitcoin Network Demand Ensemble Trading Strategy

3.5.1 Strategy Construction

The four network demand metrics outlined in Section 3.3 are combined together as an Ensemble long-only BTC trading strategy with the signal generation rules outlined in Section 3.4.1 and the optimal parameters identified using the procedure explained in Section 3.4.2. The diversity of the indicators and the way signals are generated, makes them ideal for being combined in an Ensemble trading strategy. When traded using BTC, this Ensemble trading strategy aims to protect investors against the risk of large drawdowns, in the price of BTC, and boost overall risk-adjusted returns. The BYTE algorithm incorporates the four network demand metrics using six different rules (Table 3) in a linear fashion, to give an overall allocation score which serves as an indicator of overall network demand.

Network Demand Indicator	BTC Long-only Trading Rule	Score
Fees	Short MA > Long MA Short MA > Medium MA	1 1
Transaction Value $	Short-1 MA > Short-2 MA Short MA > Medium MA	1 1
Velocity	12 Week Rolling > 600%	1
Miner's Rolling Inventory	Change in Inventory > 100%	1
Total Score		**6**

Table 3: The 6 rules that comprise the BYTE Bitcoin Network Demand Ensemble Trading Strategy

Using the total score calculated using these six rules, we can define two core allocation strategies[15] based on the weighting methodology (Variable or Fixed) as summarized in Table 4. In both cases, the BYTE Bitcoin Network Demand Ensemble Trading Strategy goes long BTC when fundamental network demand is strong and sells out of BTC on weakness, however, in Strategy 1 the allocation to BTC is variable [0, 50,100%] whereas in Strategy 2 it is binary [0, 100%].

[15] It is possible to have more sophisticated rules, especially to reduce the number of trades, however these are the two simplest ones in keeping with the *KISS Principle* of trading strategy design.

Byte Strategy	Weighting	Allocation Rule based on Score
1	Variable	**Total Score = 0, 1 or 2** → Network Demand low → **100% Cash** **Total Score = 3** → Network Demand moderate → **50% Cash and 50% Bitcoin** **Total Score = 4, 5 or 6** → Network Demand high → **100% Bitcoin**
2	Fixed (Binary)	**Total Score = 0, 1, 2, 3** → Network Demand low → **100% Cash** **Total Score = 4, 5, 6** → Network Demand low → **100% Bitcoin**

Table 4: BYTE Bitcoin Network Demand Ensemble Trading Strategy 1 and 2

3.5.2 Strategy Evaluation

The performance of both trading strategies is presented in Section 4 and evaluated in Section 5. The strategies are tested over the period 1st July 2014 – 26 April 2020 with key return, risk and risk-adjusted return metrics computed for evaluation. The results are compared with a passive (buy-and-hold) investment in BTC over the same period as well as Gold, World Equities and Global Government Bonds for the sake of completeness.

▶ Section 4: Results

In this section we present the results of the BYTE Bitcoin Network Demand Ensemble Trading Strategy 1 and 2 outlined in Section 3.5.1. Figure 4 shows the long term return of these strategies rebased to 100 as at 1st July 2014. Figure 5 shows the Annual Rolling CAGR of the same strategies compared with a passive investment in BTC whereas Figure 6 and Figure 7 shows the Annual Rolling Drawdown and the Annual Rolling Sharpe Ratio of the same strategies respectively. Table 5 summarizes the statistical performance of the two ensemble trading strategies compared with the performance of trading strategies constructed using the underlying network demand indicators and key comparison benchmarks.

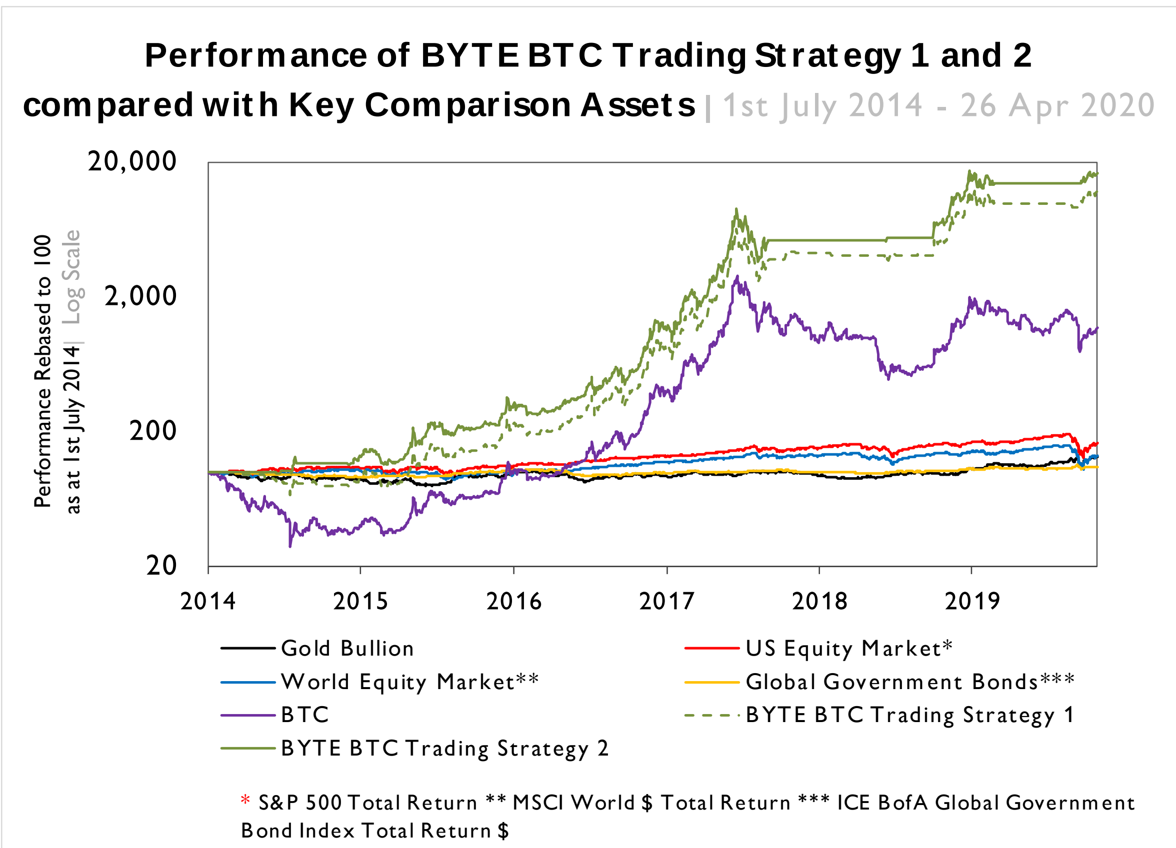

Figure 4: Performance of BYTE Bitcoin Network Demand Ensemble Trading Strategy 1 and 2 compared with key comparison benchmarks including BTC, Gold Bullion, World and US Equities and Global Govt. Bonds

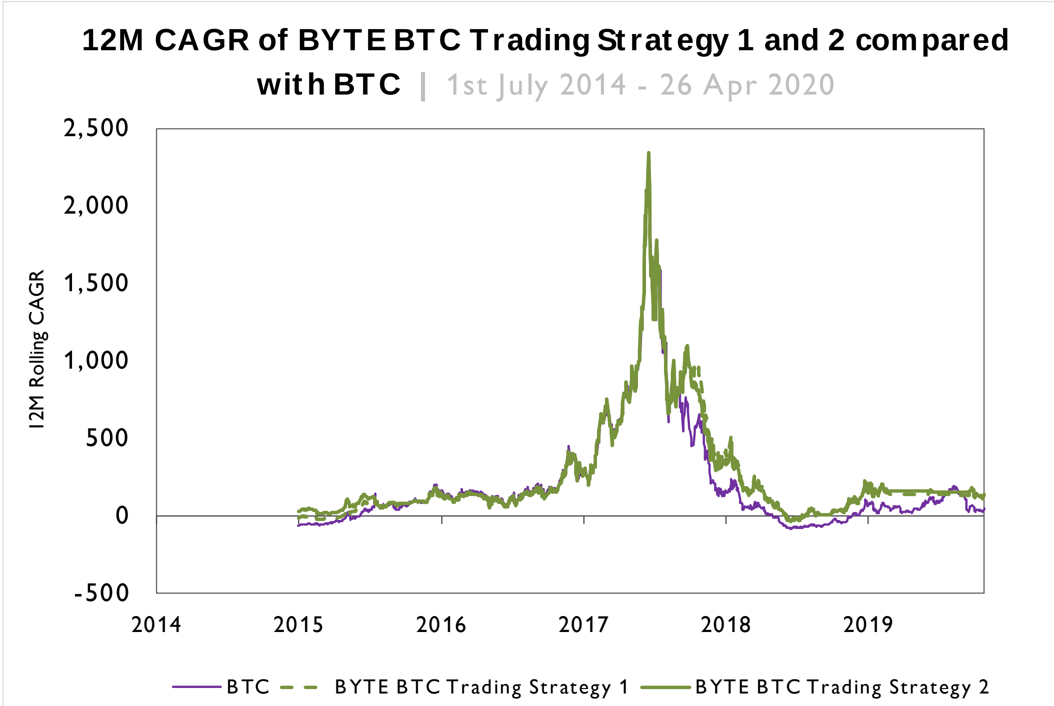

Figure 5: 12M Rolling CAGR of BYTE Bitcoin Network Demand Ensemble Trading Strategy 1 and 2 compared with a passive investment in BTC

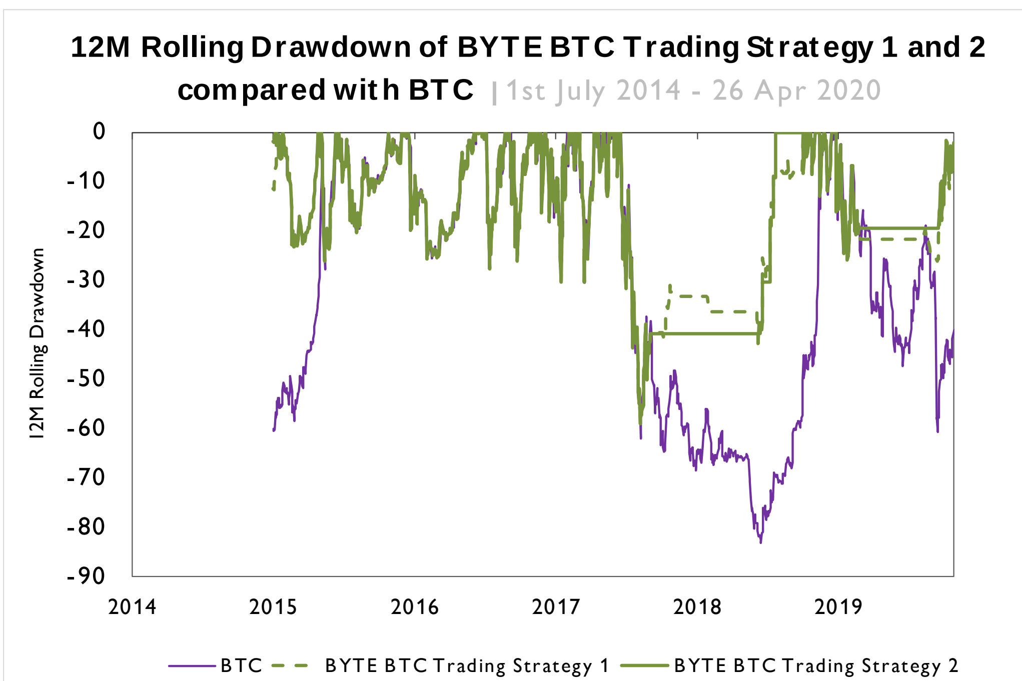

Figure 6: 12M Rolling Drawdown of BYTE Bitcoin Network Demand Ensemble Trading Strategy 1 and 2 compared with a passive investment in BTC

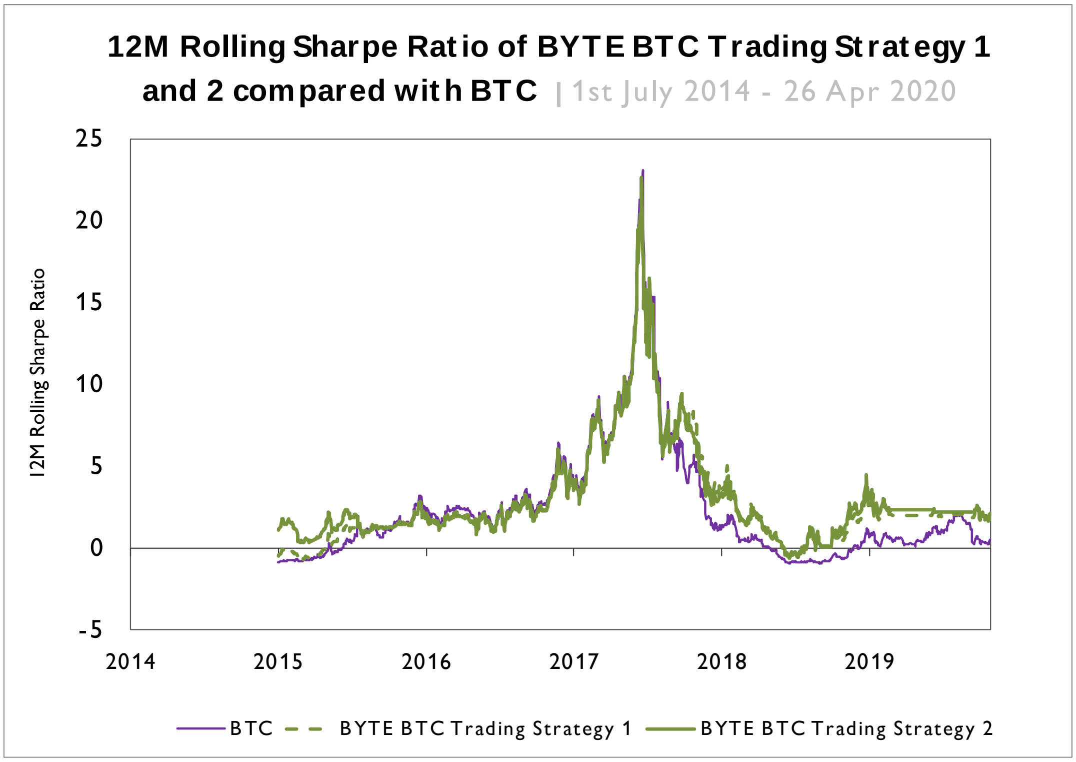

Figure 7: 12M Rolling Sharpe Ratio of BYTE Bitcoin Network Demand Ensemble Trading Strategy 1 and 2 compared with a passive investment in BTC.

		BENCHMARKS					ENSEMBLE		BTC NETWORK DEMAND INDICATORS					
	01.Jul.14 to 26.Apr.20	Gold Bullion	US Equity Market	World Equity Market	Global Govt. Bonds	BTC	BYTE BTC Trading Strategy 1	BYTE BTC Trading Strategy 2	Transaction Value $ Short-1 MA > Short-2 MA	Transaction Value $ Short-3 MA > Medium MA	Fees $ Short MA > Long MA	Fees $ Short-2 MA > Medium MA	Velocity 12W > 600%	MRI > 100%
RETURN	CAGR	4.5	8.9	5.0	1.5	52.9	128.5	140.6	60.6	70.7	116.9	136.1	104.3	78.0
RISK	Standard Deviation	15.8	21.4	18.0	7.0	83.2	69.3	68.2	65.9	73.9	65.2	67.6	76.3	79.4
	Maximum Drawdown	-21.4	-33.8	-34.0	-11.2	-83.1	-59.2	-59.2	-63.6	-60.1	-47.8	-59.2	-69.1	-76.9
RISK ADJUSTED RETURN	Sharpe Ratio*	0.1	0.3	0.1	-0.3	0.6	1.8	2.0	0.9	0.9	1.7	2.0	1.3	0.9
	Calmar Ratio	0.2	0.3	0.1	0.1	0.6	2.2	2.4	1.0	1.2	2.4	2.3	1.5	1.0

Table 5: BYTE Bitcoin Network Demand Ensemble Trading Strategy 1 and 2 Performance Statistics compared with BYTE Bitcoin Network Demand Indicators Trading Strategy performance and key comparison benchmarks. Risk free rate used for Sharpe Ratio = 3.5%. Results colour-coded using heatmap; red = bad; green = good.

► Section 5: Discussion

5.1 BYTE BTC Ensemble Trading Strategy

The Bitcoin Network Demand Ensemble Trading Strategy (Section 3.5) incorporates the four network demand indicators outlined in Section 3.3 but does so by double-weighting Fees and Transaction Value Bitcoin Network demand (Section 3.5.1). These weights are not a deliberate design of the strategy but rather an unintended consequence of the trading rules. These rules and parameter combinations are designed to capture the Short, Medium and Long term trends that exists in these indicators. However, the final choice of parameter values (e.g. Velocity > 600%) was determined by following the optimization guidelines outlined in Section 3.4.2.

For the other network demand indicators – Velocity and Miner's Rolling Inventory – only a single level-crossover rule was utilized as it was determined to be more important than the trend when utilizing these indicators for trading BTC. At the same time, by using a variety of trading rules, the aim was to increase diversity in order to create a more robust Ensemble.

The MRI network demand indicator is used to generate BTC trading signals when it exceeds 100%. At first glance, it may appear counterintuitive to use a high MRI reading as a reliable indicator of an increase in network demand (Section 3.5.1) – considering that a high MRI reading is also indicative of heavy miner selling (Section 3.3.4). However, the thing to remember is that miners are savvy market participants who have invested vast time and money into their operations and thus want to achieve a good selling price on their newly minted coins (Morris, 2020b). In this sense, a high MRI reading is not contrary to strong network demand as it suggests a strongly bid market which miners are comfortable selling into. Conversely, when the bid fades, miners hold back as they await better selling opportunities, leading inventories to rise and MRI to fall.

5.2 Performance of the Ensemble Trading Strategies

An analysis of the performance of the BYTE BTC Ensemble Trading Strategies (Section 4 – Table 5) reveals that Strategy 2 (Fixed weights strategy) outperforms Strategy 1 (variable weights strategy) on both a return and risk-adjusted return basis. This appears to suggest that the best use of the Network Demand indicators as a composite BTC trading strategy is with Fixed (binary) weights rather than variable weights (Section 3.5.1 – Table 4).

The best performing Ensemble Trading Strategy is also the best performing overall, followed by Fees as the best individual Bitcoin Network demand trading strategy. The latter recorded a CAGR of 136.1% over the entire test period compared with the Ensemble Trading Strategy 2 which registered a return of 140.6%. The risk-adjusted return of these two strategies is broadly on par, both on a Sharpe and Calmar basis (Section 4 – Table 5). Whilst both these measures define return in terms of CAGR, the former metric measure risk in terms of Standard Deviation whilst the latter defines it in terms of the Maximum Drawdown (Section 8.1.4 - 8.1.5). At the same time, both strategies are seen to deliver a significantly higher (more than double) return and risk-adjusted return compared with a passive investment in BTC (Section 4 – Table 5). The BTC Ensemble Trading Strategy 1 lags the performance of BTC Ensemble Trading Strategy 2 on both a return and risk-adjusted return basis, however it outperformed a passive holding of BTC by more than double.

The superior performance of the Fees network demand indicator is not surprising given its direct role as an indicator of the level of economic activity within the Bitcoin Network as explained in Section 3.3.1. The next best performing individual network demand indicators are Velocity and MRI in terms of return and risk-adjusted return. It is noteworthy that whilst they significantly underperform the Fees network demand indicator, including them as part of the Ensemble Trading Strategies does not dilute the performance of the latter. In this sense, trading the Ensemble strategy is superior to trading any single network demand indicator, as it allows us to capture the information contained in each of these indicators without being swayed by the performance of any one of them.

BTC is an inherently volatile asset class, over four times as volatile as World and US Equities and around twelve times as volatile as Global Government Bonds (Section 4 – Table 5). Even when traded using the Ensemble trading strategies, the Maximum Drawdown associated with trading this asset class is around twice that of the World Equity Market, measured over the same period. Notwithstanding, investors who have been able to tolerate the risk of trading BTC have found that the returns from doing so have been more than commensurate for the risk taken[16]. This is shown by the risk-adjusted performance of the Ensemble BTC trading strategies, compared with traditional asset classes such as World and US Equities, Global Government Bonds and Gold Bullion (Section 4 – Table 5). The risk-adjusted performance of the Ensemble Strategies stands head-and-shoulders above the latter.

5.3 Future Work

The BYTE Network Demand indicators considered in this paper are the most important ones, the trading rules used elementary and the Ensemble techniques very simple. Despite their simplicity, the superior performance results of the Ensemble trading strategy illustrate how a simple rules-based composite trading strategy can be used to exploit the network effect – using suitable Bitcoin Network demand indicators – to deliver better risk-adjusted returns and lower drawdowns than a passive holding of BTC.

We believe that this strategy can be further improved by using more sophisticated machine learning algorithms, feature transformation techniques[17] as well as by incorporating other asset class data. In future, we intended to build on this work by considering each of these different elements to assess how they can further improve the Ensemble BTC trading strategy to deliver better risk-adjusted returns and lower drawdowns compared to a passive holding of BTC.

[16] However please be aware that past performance is not a guarantee of future performance.

[17] *Feature transformation* refers to the creation of new features (indicators) from existing ones.

► Section 6: Conclusion

This paper has introduced readers to BTC and the importance of the "Network Effect" as an important determinant of its value. As the value of a network has been shown to be directly related to its level of activity, it has been argued that network demand indicators can be applied to an investment strategy. When demand on the bitcoin network is strong, the strategy is long bitcoin. When network demand is weak, the strategy holds an interest accruing cash position.

Four key BYTE indicators have been used to measure network demand and these have been applied over two variants of Ensemble trading strategies. The historical performance of these trading strategies gives us confidence that the BYTE set of indicators can be used to successfully capture the Bitcoin Network effect, and deliver better risk-adjusted returns and lower drawdowns than a passive holding of BTC.

► Section 7: References

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► Section 8: Appendix

8.1 Performance Statistics

8.1.1 Compound Annual Growth Rate

A measure of the annualized return of an investment calculated as:

$$= \left[\left(\frac{Ending\ Portfolio\ Value}{Starting\ Portfolio\ Value} \right)^{\frac{1}{Duration\ of\ Investment\ in\ Years}} \right] - 1$$

A higher CAGR is indicative of a larger return on Investment.

8.1.2 Standard Deviation (σ)

A statistical measure of the risk of an investment based on an assessment of how much returns deviate from the mean return over a given period. It is calculated as:

$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(R_i - \overline{R})}{N-1}}$ where Ri = return of an investment over a discrete period e.g. monthly

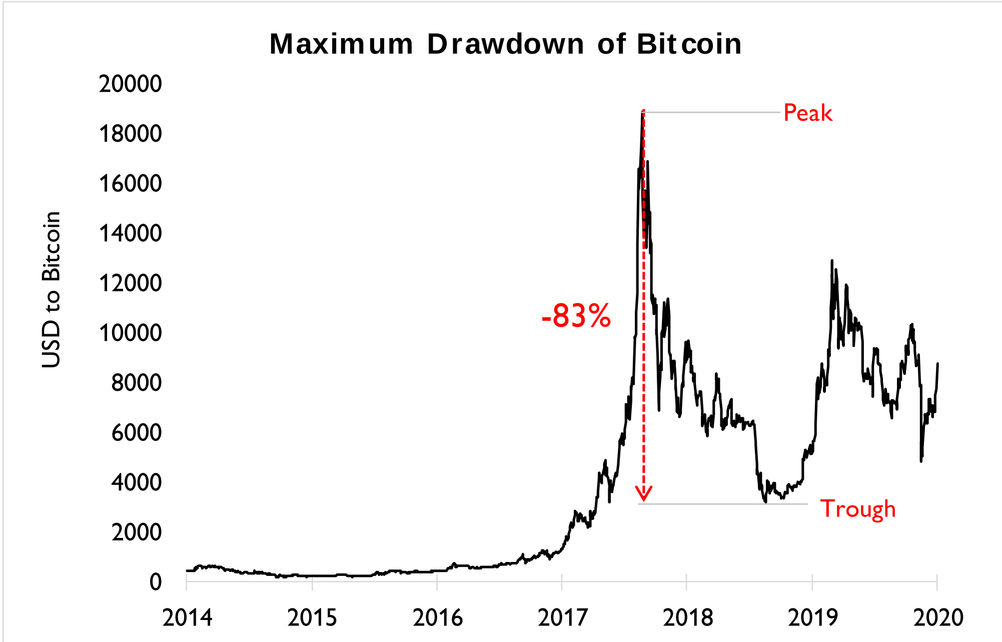
$\overline{R}$ = the mean return

N = Number of periods

A higher standard deviation is indicative of a more volatile (risky) investment.

8.1.3 Maximum Drawdown

Maximum Drawdown is another key measure of the risk of an investment and one that is more intuitive than Standard Deviation. It is calculated as the peak-to-trough loss of an investment before a new peak is reached as shown below. An investment that has incurred a larger maximum drawdown has historically been more risky. Minimizing drawdowns is a vital component of preserving and growing capital over the long term.



8.1.4 Sharpe Ratio

A key risk-adjusted performance measure of an investment calculated as the excess return generated by an investment (i.e. return in excess of return on cash) divided by the risk of the investment (standard deviation). The higher the Sharpe Ratio of an investment the higher the risk adjusted return i.e. excess return per unit of risk taken.

$$Sharpe\ Ratio_{\ Investment} = \frac{CAGR_{\ Investment} - CAGR_{\ Cash}}{\sigma_{\ Investment}}$$

8.1.5 Calmar Ratio

A key risk-adjusted performance measure of an investment calculated as the CAGR divided by the Maximum Drawdown. A Higher (lower) Calmar Ratio is indicative of an investment with a higher (lower) risk adjusted return.

$$Calmar\ Ratio_{\ Investment} = \frac{CAGR_{\ Investment}}{Max\ Drawdown_{\ Investment}}$$

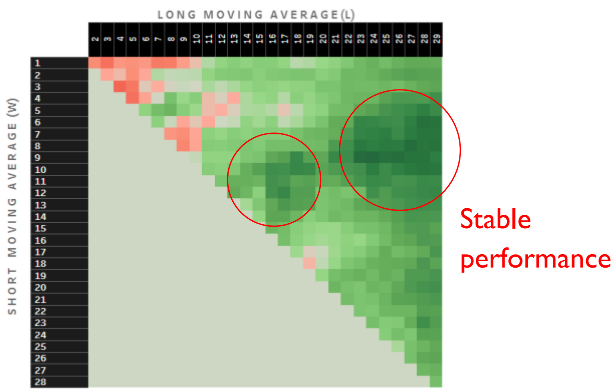
8.1.6 Number of Trades

The number of trades placed when dealing in an investment. One trade is equivalent to a buy-and-hold strategy whilst a very large number of trades is indicative of a very active trading strategy,

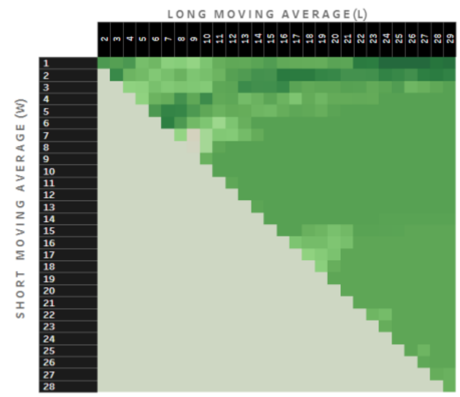
8.2 Parameter Optimisation Results

8.2.1 Fees Performance Results (Relative BTC Passive Holding)

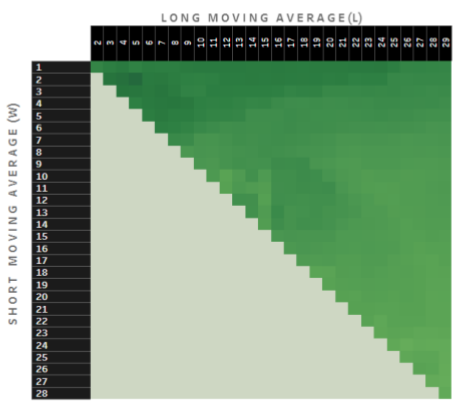
- Compound Annual Growth Rate



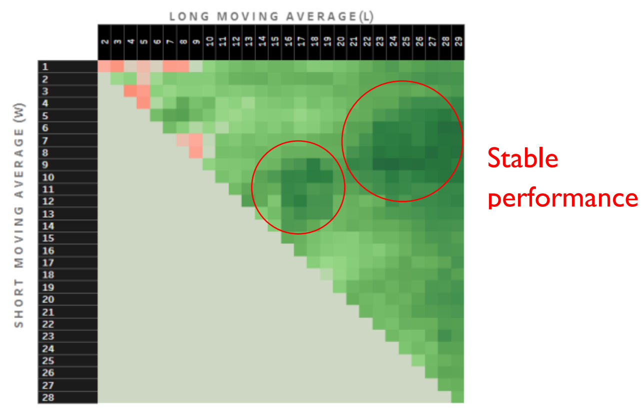
- Maximum Drawdown



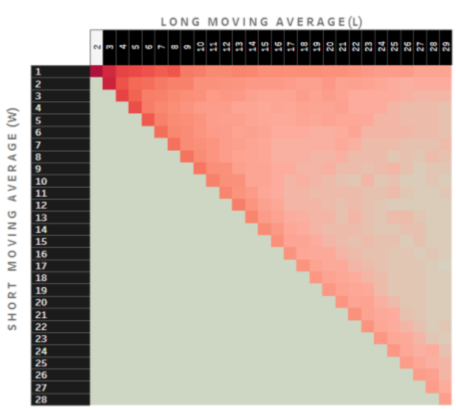
- Standard Deviation



- Sharpe Ratio



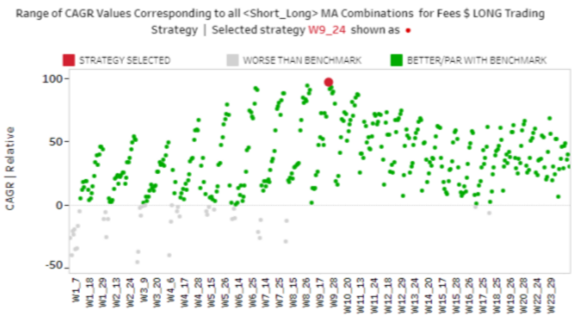
- Number of Trades



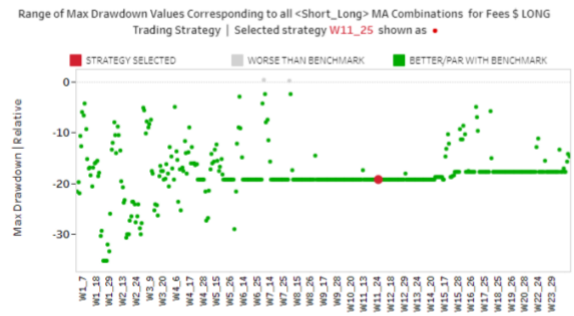
- Interpretation

The heatmaps above show the performance statistics of BTC traded using the ByteTree Fee Indicator with signals generated using a double-MA crossover strategy for various short (W) and Long MA Combinations. The returns are shown relative to a passive holding of BTC. Red implies a performance lag whereas green shows excess returns.

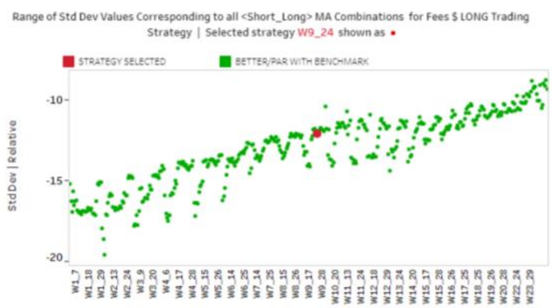
Compound Annual Growth Rate



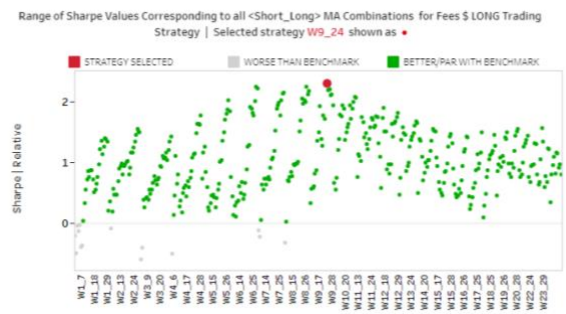
Maximum Drawdown



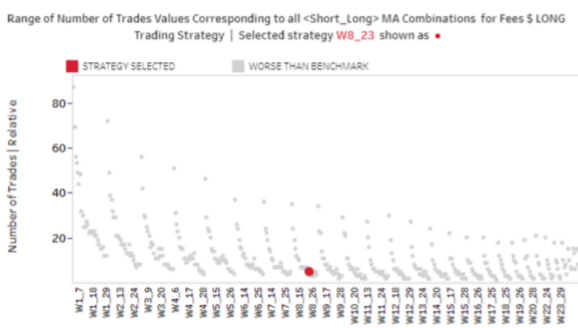
Standard Deviation



Sharpe Ratio



Number of Trades



Interpretation

The scatterplots above show the performance statistics of BTC traded using the ByteTree Fee Indicator with signals generated using a double-MA crossover strategy for various short (W) and Long MA Combinations. The returns are shown relative to a passive holding of BTC. Red implies a performance lag whereas green shows excess returns.

8.3 About ByteTree

ByteTree is a leading provider of institutional-grade crypto-asset data. The ByteTree investor terminal tracks over 80 metrics for bitcoin in real-time. ByteTree's on-chain data platform was conceived in 2013 as a tool to assist a multi-asset fund manager with in managing risk in his portfolio. After yielding great success, the tool launched as a publicly accessible investor terminal in 2018. ByteTree brings rigorous practices in data quality and delivery to crypto-asset investing. The Terminal is currently the leading source of real-time data for UTXO-based blockchain networks.

8.4 Disclaimer

This document does not constitute an offer of investment advisory services by Crypto Composite Ltd. nor does it constitute an offering of limited partnership interests in the Fund; any such offering will be made solely pursuant to the Funds private placement memorandum. No undertaking, warranty or other assurance is given, and none should be implied, as to, and no reliance should be placed on, the accuracy, completeness or fairness of the information or opinions contained in the Document. Investments in crypto-assets and in the BYTE strategy are speculative and involve a high degree of risk. You should be aware that you could lose all, or a substantial amount, of your investment in the strategy. Crypto-assets can be extremely volatile and subject to rapid fluctuations in price, positively or negatively. Investment in one or more crypto-assets may not be suitable for even a relatively experienced and affluent investor and independent financial advice should be sought where applicable.