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Optimizing Returns in Cryptocurrency Markets: A Comparative Analysis of Complex Technical Trading Rules and Buy-and-Hold Strategies

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ABSTRACT

This study aims to examine profit optimization in a highly volatile cryptocurrency market. It performs a comparative analysis between Complex Technical Trading Rules (CTTRs) and the Buy-and-Hold (B&H) strategy when trading Bitcoin and 10 alt coins, taking data for all coins and tokens from the daily close price of January 1, 2021, to December 31, 2022. The results proved that the CTTRs strategy offers forecasting power when trading Bitcoin and alt coins, causing the trade to outperform the traditional or default B&H strategy. However, the CTTRs could not reject the weak form of the Efficient Market Hypothesis (EMH), so the theory remains intact and unchallenged by the CTTRs alone, which primarily relies on Technical Analysis (TA). This outcome suggests that combining Fundamental Analysis (FA) with TA may be necessary to overcome the weak form of EMH. Notably, despite their inability to challenge the weak form of EMH, CTTRs demonstrated superior performance during the trending cryptocurrency bull market observed throughout the research period. Our study provides insights to benefit investors regarding the CTTRs and B&H strategy in the cryptocurrency market and explores the potential to generate abnormal returns with the CTTRs.

JEL Classification: G11, G12, G14

Keywords: Buy & Hold Strategy; Complex Technical Trading Rules; Cryptocurrency Market; Simple Technical Trading Rules; Technical Analysis

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INTRODUCTION

Cryptocurrency rapidly increased in popularity as an investment destination in 2023, with close to 20,000 types of cryptocurrencies, more than 511 centralised or decentralised exchanges, and a staggering USD 1.85 trillion in market capitalisation. This rapid growth has solidified the cryptocurrency market as an important market in the financial industry. Despite cryptocurrency being created only 14 years ago, the entire cryptocurrency market is currently constituting 20% of the gold market capitalisation, with Bitcoin being the first peer-to-peer and decentralised digital currency (Lorenzo and Arroyo, 2022; Nakamoto, 2009).

Cryptocurrency, unlike traditional assets, lacks physical assets and government support for its value. Thus, in many countries, the cryptocurrency market remains highly speculative and volatile (Corbet et al., 2019; Lorenzo et al., 2022). Due to its relative inefficiency compared to other markets, such as gold, equity, bonds, commodities, and forex, the cryptocurrency market is currently an attractive investment opportunity for institutional and retail investors (Grobys et al., 2021). The US government has recently decided to lead the global cryptocurrency innovation and serve as the primary player in this new revolution (Sen, 2024). However, no laws in the US are yet available to protect investors from losing resources.

As the cryptocurrency market evolves, early-stage adoption of this emerging technology requires regulatory support to protect investors (Zhang, 2020). The lack of regulation and infrastructure may lead to greater risk. Because cryptocurrency's potential remains high (Hasan et al., 2022), investors must navigate the complexities of the market carefully to capitalise on its potential benefit. The collapse of the US Signature Bank in 2023 is a good example of the need to carefully evaluate the potential danger and risks associated with investing in cryptocurrency-related companies and banks.

Currently, there is no clear path to Fundamental Analysis (FA) in cryptocurrency. While many hedge funds and institutional asset managers are currently exploring the decision to include cryptocurrency-related assets in their portfolios (Fang et al., 2022), institutional investors disagree on how best to analyse and approach this new asset class. This study investigates profitability optimization using the Complex Technical Trading Rules (CTTRs) and Buy-and-Hold (B&H) strategy in generating profits in the cryptocurrency market. It also evaluates the performance of risk and volatility associated with both strategies. The study challenges the weak form of the Efficient Market Hypothesis (EMH), which concludes that investors cannot constantly generate returns in any market (Fama, 1970), including the cryptocurrency market, with only Technical Analysis (TA) (Ahmed et al., 2020). Many studies have concentrated on successful simple technical trading rules (STTRs), such as the Moving Average (MA) and Trading Range Breakout (TRB), particularly in the context of Bitcoin (Gerritsen et al., 2020). However, other STTRs have frequently failed to generate positive returns in various equity markets (Gerritsen, 2016), thereby fulfilling predictions from the weak form of the Efficient Market Hypothesis (EMH).

Despite the growing attention in cryptocurrency trading and investment, few studies have examined the application of CTTRs due to their high complexities in digital currency markets. This study intends to further the analysis by encompassing a much broader range of cryptocurrencies and applying the CTTRs. The analysis period spans from January 1, 2021, to December 31, 2022, at which point the effectiveness of the CTTRs and B&H strategy are evaluated. This study combined five popular STTRs, namely Linear Regression Channel (LRC), Advance-Decline Line (ADL) with Bollinger Band (BB), On-balance Volume (OBV) with BB, and Commodity Channel Index (CCI) with BB.

The findings of this study have enriched the existing academic literature on the efficiency of the cryptocurrency market and its potential for generating positive returns with CTTRs. Traders and investors aiming to navigate the highly volatile and uncertain cryptocurrency market can gain valuable insights into dynamic support and resistance levels by employing the CTTRs strategy. This approach helps identify potential price movements both upwards and downwards and guides more informed decision-making in such unpredictable conditions. By challenging the weak form of the EMH (Fama, 1970), this study provides insights into the potential of CTTRs and offers valuable future price projections to traders and investors seeking to capitalise on this emerging asset class.

The remainder of the paper is as follows: the next section presents the review of literature. This is followed by a section on the research methodology and data of this study. Subsequently, the estimation results for the full sample and subsample are discussed. The final section concludes the paper.

REVIEW OF LITERATURE

Application of Simple Technical Trading Rules (STTRs)

The academic literature asserts that applying the STTRs of TA in equity may or may not generate profit depending on the types of STTRs. Some researchers conclude that the STTRs of TA have no value and cannot result in constant returns, with some arguing that STTRs can generate profit in short trading. However, many researchers lack awareness of the popular theory that EMH challenges the validity of STTRs of TA, arguing that the market is efficient all the time and trades cannot constantly generate positive risk-adjusted returns by using TA alone. Many popular applications of STTRs mostly lead to negative returns or losses.

The literature has only examined some of the popular STTRs in the equity market, but not for cryptocurrency. The existing research has not explored more than 100 STTRs from the Tradingview.com charting platform in detail and has avoided CTTRs due to the complexity involved in researching such a topic. The popular STTRs examined include Moving Average Convergence Divergence (MACD), Channel Breakout, and RSI. Other STTRs applied and examined include Momentum Strategy, Relative Strength, Channel Break Out, Triangle, Rectangle (Jin, 2021), Filter Rules, MA, Support Resistance, Channel Breakout, Relative Strength Index (Sermpinis et al., 2021), OBV (Arman et al., 2021), Exponential Moving Average (Souza et al., 2018), Momentum (Lin, 2018), Trading Range Breakout (TRB), Moving Average Crossover, MACD, Rate of Change (Gerritsen, 2016), Candlestick Pattern Head and Shoulder (Friesen et al., 2009), Exponential Moving Average, MACD (Cocco et al., 2019), Stochastic Oscillator, William Percentage Range, BB, Rate of Change (Loo, 2020), Bullish and Bearish Engulfing Candle (Heinz et al., 2022), and Piecing Line and Dark Cloud Pattern (Alanazi and Alanazi, 2020).

Among the plethora of techniques examined in the scholarly discussion of STTRs, only a few, such as the Moving Average (MA) and TRB, have proven successful in both generating profits and refuting the weak form of the Efficient Market Hypothesis (EMH), as evidenced by Gerritsen et al. (2020). These strategies have been the focus of significant research within both equity markets (Arman et al., 2021) and the Bitcoin trading space (Ahmed et al., 2020). However, it is imperative to avoid premature conclusions regarding the utility of STTRs in trade and investment solely based on the existing body of literature, since many STTRs have not been thoroughly investigated. A comprehensive evaluation of the spectrum of STTRs is essential before drawing conclusive judgments about the value of TA.

This expanded inquiry is particularly critical in light of the complexities presented by incomplete FA information in the cryptocurrency market. Exclusive reliance on TA, implemented through CTTRs, can indeed improve trading results. However, overcoming the weak form of the EMH typically requires the integration of both TA and FA, particularly when TA alone falls short of capturing all relevant market information (Titan, 2015). Despite the effective combination of TA and FA, it is important to note that this approach does not ensure profitability in markets governed by semi-strong and strong forms of EMH (Fama, 1970). Therefore, merging these analytical frameworks not only yields a more comprehensive understanding of market conditions but also potentially enhances the ability to surpass the weak form of EMH, offering a strategic advantage in the intricate and volatile cryptocurrency markets.

The Effectiveness of Proven Technical Trading Rules (VMA, FMA, and TRB) in Cryptocurrency

Numerous studies have explored the predictability of financial asset classes based on past returns, but limited research has focused on the application of STTRs in cryptocurrency markets, even less when CTTRs are studied in the cryptocurrency market. Corbet et al. (2019) investigated the performance of three popular trading rules, namely the Variable-length Moving Average (VMA), Fixed-Length Moving Average (FMA), and TRB, when applied to high-frequency Bitcoin returns. The findings suggest that the VMA strategy provides the most significant benefit, with results in rejecting the weak form of EMH. FMA and TRB, however, do not offer the same level of support compared to the VMA strategy. The results imply that certain STTRs can present evidence of predictive power and may aid in producing constant returns for Bitcoin traders and investors. The ability to profit with VMA in the literature above does not account for factors such as attention, trading volume, other cryptocurrencies, geopolitical risks, economic uncertainty, stock market uncertainty, and energy/commodity prices (Gerritsen et al., 2020).

Ahmed et al. (2020) focus on the VMA STTRs and employ the daily price data of the 10 most-traded cryptocurrencies, with some exhibiting a ‘privacy function’. The study reveals that the VMA STTRs were successful only when applied to Dash, generating annual returns of 14.6%−18.25% more than the simple B&H benchmark strategy. However, the STTRs did not yield greater positive returns than a B&H strategy on an aggregate level. This shows that the study was unsuccessful in attempting to trigger abnormal returns and reject the weak form of EMH through the application of STTRs.

In conclusion, these studies highlight the potential of STTRs in cryptocurrency markets and suggest that certain strategies, such as VMA, offer predictive power and generate constant returns for traders and investors. However, further research is necessary to account for various market factors to evaluate the effectiveness of VMA STTRs, especially in the context of CTTRs for the equity or cryptocurrency markets.

RESEARCH METHODOLOGY

STTRs and CTTRs

CTTRs involve sophisticated strategies that rely on technical indicators and algorithms to make trading decisions. They are designed to build upon simpler strategies by integrating multiple STTRs and conditions along with other types of analysis into a comprehensive strategy. This approach often involves automated trading systems that take action to execute trades based on pre-set criteria from technical indicators, combining multiple STTRs into a cohesive algorithmic approach (Chuang et al., 2024).

We explore five popular types of STTRs that are gaining popularity but have not been widely researched. To challenge the weak form of the EMH, our study examines STTRs not widely researched, like the On-balance Volume (OBV) and Advance Decline Line (ADL) strategies. These methods have been applied to defeat weak EMH (Corbet et al., 2019); however, the STTRs strategies we investigate in this study have received less attention in academic literature. Our study aims to utilize CTTRs to achieve a similar objective to these strategies while enhancing the return generated by STTRs.

This study examines the first family of STTRs, which includes the fusion of two widely popular technical rules, ADL and the BB. Introduced by Zakon and Pennypacker (1968), the ADL tracks the number of positive stocks for a given day. When more than 50% of the total number of stocks for the day is positive and profitable, then the day's value is added to the cumulative ADL value. Conversely, if 50% of the total number of stocks for the day is negative and results in losses, this value is subtracted from the cumulative ADL value. When the ADL breaches the lower band of the BB, a buying signal is created, while a selling signal is issued to traders when the ADL line breaches the upper band of the BB. For this study, we utilise the default settings for the ADL and a length setting of 15 for the BB.

A second rule belongs to the most widely used trading rule, On-Balance Volume (OBV) (Granville, 1963), which is the indicator based on trading volume. In this second STTRs, we do not operate OBV alone but combine it with BB (Bollinger, 2001). OBV alone measures volume trading for the day. If more than 50% of the stock price is up, then a positive volume number is added to the cumulative OBV value, and vice versa when the price for that day is negative. When the OBV line ruptures the bottom BB standard deviation line, a buying signal is furnished, and a selling signal appears when the OBV line breaches the upper BB standard deviation line. For the purpose of this study, we utilise the default setting for the OBV with a Simple Moving Average of 5 as a smoothing parameter and a length setting of 15 for the BB.

In this study, the Commodity Channel Index (CCI) and the BB are explored as a third rule that combines these two widely popular trading rules. The CCI was first introduced by Lambert (1980) and is utilised to measure overbought and oversold conditions in the market. When the CCI line is above 100, the market is considered overbought; however, when it falls below -100, it is considered oversold. Traders can start buying when the CCI line fractures the BB bottom standard deviation line. Conversely, traders can sell when the CCI breaches the upper standard deviation line, indicating a potential downward trend. In this study, we utilise the length 20 setting for the CCI with a Simple Moving Average of 5 for the smoothing parameter and a length setting of 15 for the BB.

We investigate a fourth rule that utilises the Linear Regression Channel (LRC) (Kosakovsky, 2021). For this study, we use the length setting of 600, although other parameters and settings such as 500, 420, and 300 were also considered. The LRC rule is applied to price action charts. A buying call is initiated when the price breaches the bottom LRC line of 2 standard deviations. The LRC top and bottom standard deviation setting for the Upper Deviation is at 2 and that for the Lower Deviation is also at 2. Conversely, a selling call is initiated when the upper standard deviation line is breached. It is commonly recommended that investors buy into the market when the price action passes the bottom standard deviation line for the third time. However, these textbook rules are not always accurate and helpful for traders and investors. We assume a length setting of 600 for the LRC to simplify the trading rules. By incorporating this rule into our analysis, we can provide a more comprehensive examination of the STTRs.

BB is the fifth popular STTR created by Bollinger (2001) and is used in this study to identify potential overbought and oversold conditions in the market. It is also sometimes used to determine an asset's volatility. The BB of STTRs consists of three lines: a simple default MA line with a parameter set to 20 days, an upper non-linear band two standard deviations from the default 20-day MA line, and a lower non-linear band two standard deviations below the MA line. When the price action approaches the upper bands, traders can use this as an opportunity to sell, and when the price action breaches the lower band, then traders can use it as a buying signal.

In this study, we investigate the effectiveness of CTTRs, which comprise all the STTRs of ADL+BB, OBV+BB, CCI+BB, and LRC. To buy, we consider a buying signal from LRC with supported signals from ADL+BB and either OBV+BB or CCI+BB. The selling signal from this paper CTTRs is the reverse of the buying signal mentioned above with minor differences. The capital for each purchase of Bitcoin and each of the 10 alt coins when CTTRs is triggered is USD100.00. All B&H strategy purchase capital is also USD100.00.

Buy the Dip (BTD)

According to Bonini et al. (2022), Buy the Dip (BTD) is an investment strategy that involves purchasing an asset after its price has declined, with the expectation that it will rebound and increase in value. This approach is based on the belief that price drops are temporary and that the asset's fundamental value remains intact. Investors who BTD seek to accumulate more shares at a discount, betting on the market's recovery to generate profits. This strategy is commonly used in stock markets; however, can be applied to any financial asset, including cryptocurrencies. It assumes that the investor can accurately identify the bottom of the market dip, which can be risky if the asset continues to decline in value.

This study signals a buy when the price almost breaches the bottom LRC line of 2 standard deviations with 10% or less to go. The rules must have supported signals from OBV+BB or CCI+BB and ADL+BB buying signals to purchase 40% of USD100. Meanwhile, the remaining buying of the 60% will happen when the price action increases to 30% from the first 40% purchase.

The other 60% buying scenario in this study applies the BTD buying calls when the price action further drops from the first 40% purchase. The price action needs to breach the LRC lower standard after the first 40% purchase, with the supported signal of buying also from OBV+BB or CCI+BB and ADL+BB. The study buys the remaining 60% at this BTD rule. The selling signal is slightly different from the CTTRs buying signal.

Table 1 CTTRs buying calls definition

Buying Calls	1st Sub Purchase	2nd Sub Purchase	Total Purchase	Purchase without BTD or without sub purchases
1st Buy with CTTRs signal	1st buy of 40% with USD40.00	1st buy of 60% with USD60.00	100% = 1st buy of 40% + 1st buy of 60%	1st buy 100% with USD100
2nd Buy with CTTRs signal	2nd buy of 40% with USD40.00	2nd buy of 60% with USD60.00	100% = 2nd buy of 40% + 2nd buy of 60%	2nd buy 100% with USD100
3rd Buy with CTTRs signal	3rd buy of 40% with USD40.00	3rd buy of 60% with USD60.00	100% = 3rd buy of 40% + 3rd buy of 60%	3rd buy 100% with USD100

Table 1 shows the CTTRs' 1st buy of 40% is the 1st sub-purchase, and the CTTRs' 1st buy of 60% is the 2nd sub-purchase in the first buying call. The CTTRs' 2nd buy of 40% is the 1st sub-purchase, and the CTTRs' 2nd buy of 60% is the 2nd sub-purchase in the second buying call. The CTTRs' 3rd buy of 40% is the 1st sub-purchase, and the CTTRs' 3rd buy of 60% is the 2nd sub-purchase in the third buying call. The CTTRs' 1st Buy 100% means the purchase is made without BTD. Buy of 60% is a BTD strategy.

The CTTRs' first buy of 100% means the purchase was made without the BTD strategy, and the price action breaches the LRC 600 without dropping below 110% of {LRLOWER600} and does breach {LRLOWER600}.

Cryptocurrency Price, Return, and Trading Volume

In this study, we utilised the price history of cryptocurrencies starting from January 1, 2021. We used this date as the data on new cryptocurrencies in the market is mostly unavailable, hence data prior to this date was excluded. The data was sourced from the Tradingview platform, and our sample concludes on 31 December 2022, thereby providing us with 730 daily price observations. In addition to the daily cryptocurrency returns, we also collected the risk-free rate of return. For this, we used the 3-month US T-bill returns for the risk-free rate return. We computed the daily cryptocurrency return using the equation $r_{B,t} = In\left(\frac{B_t}{B_{t-1}}\right)$. Fig. 1 illustrates the price evolution of Bitcoin with CTTRs.

Source: tradingview.com

Figure 1 Bitcoin price evolution from August 2017 to January 2023.

Study Population

The study population commences from the price history on January 1, 2021 with data downloaded from www.Tradingview.com. Most markets trade five days per week; cryptocurrency, however, is traded 24 hours per day, 7 days per week. The last day of our population sample is December 31, 2022, giving 730 daily price observations. A list of coins and tokens studied is provided in Table 2 below.

Table 2 Coin and alt coins

No.	Coins	Symbol	Capitalisation ($)
1.	Bitcoin	BTC	$571,853,442,252
2.	Ethereum	ETH	$244,738,199,070
3.	Binance	BNB	$51,932,678,557
4.	Cardano	ADA	$18,251,634,396
5.	Avalanche	AVAX	$8,442,466,094
6.	Chainlink	LINK	$3,397,475,571
7.	Stellar	XLM	$3,349,227,594
8.	Algorand	ALGO	$3,001,509,557
9.	Ethereum Classic	ETC	$2,828,549,963
10.	VeChain	VET	$2,046,514,993
11.	Tezos	XTZ	$1,764,972,419

Note: Data from www.tradingview.com as of 23 May 2022.

Trading Strategies and Return Evaluation

We implemented five STTRs as one CTTRs in two ways. First, we initiated a long or buying position in the cryptocurrency when the CTTRs signalled a buying position. Second, we liquidated or sold the cryptocurrency when the CTTRs signalled a selling position. If there was no buying or selling signal from the CTTRs, we maintained the capital in the sideline by converting to stablecoins such as USDT. In addition, cryptocurrency exchanges such as Binance, Coinbase, and Kraken offer features that allow users to earn interest by staking their cryptocurrency coins and tokens on the exchanges. This study allocated this stablecoin in a risk-free rate environment to yield interest. Binance charges a 0.10% fee for trading on the platform as well as a 0.50% fee for instant buying or selling, so the actual fee amount depends on the amount of the trade, with higher transactions incurring higher fees.

A stop-order strategy is employed and triggered when the coin or token price drops below 25% of the initial buying price. Vezeris, Kyrgos and Schinas. (2018) suggest that the stop order threshold is around 25% based on their Average True Range (ATR) of a 6 multiplier; ATR is a measure of market volatility over a specified number of periods. The specific percentage for the stop loss depends on the ATR value at the time the position is opened and the multiplier used.

We computed two metrics, the Annualized Percentage Rate (APR) and the Sharpe ratio, to evaluate the performance of the CTTRs. The yield of positive returns is measured by the APR, where an APR value above zero is considered to yield positive returns, whereas an APR value below zero is considered to yield negative returns. The APR is calculated as:

$$APR = (b - a) / (a) \times (100) \tag{1}$$

where APR = Annual Percentage Rate, a = Buying price of crypto asset, and b = Selling price of crypto asset.

While the PNL or Profit and Loss is calculated with the following formula.

$$\begin{gathered} PNL = 0.4(APR\ 1st\ 40\%\ buy) \\ +\ 0.6(APR\ 1st\ 60\%\ buy) \end{gathered} \tag{2}$$

Or

$$\begin{gathered} PNL = 0.4(APR\ 2nd\ 40\%\ buy) \\ +\ 0.6(APR\ 2nd\ 60\%\ buy) \end{gathered} \tag{3}$$

Or

$$\begin{gathered} PNL = 0.4(APR\ 3rd\ 40\%\ buy) \\ +\ 0.6(APR\ 3rd\ 60\%\ buy \end{gathered} \tag{4}$$

The Sharpe ratio was calculated based on daily return and risk data. Specifically, the Sharpe ratio for rule i is as follows:

$$s_i = \frac{R_i}{\sigma_i} \tag{5}$$

Where $r_{B,t}$ represents the daily log return as defined on page 8, minus the 3-month US treasury-bill rate, and σi stands for the standard deviation of the daily returns for the CTTRs. The study further evaluated the performance of the CTTRs by comparing its Sharpe ratio with that of a B&H strategy for the examined cryptocurrencies. We subtract the CTTRs Sharpe ratio from the B&H Sharpe ratio to calculate the difference between the two Sharpe ratios. The Sharpe ratio is calculated by dividing the Ri excess return by the σi standard deviation of the daily returns of the CTTRs, where the Ri excess return is defined as the $r_{B,t} = In\left(\frac{B_t}{B_{t-1}}\right)$ daily log return minus the 3-month US treasury-bill rate.

We perform a statistical inference test to conclude that the CTTRs can outperform the EMH weak form. We use the T-statistic of two samples with unequal variances and a two-sided p-value to measure the statistical significance of the difference between the daily returns of CTTRs and the B&H strategy for the 10 highest market capitalisation alt coins and Bitcoin from January 1, 2021, to December 31, 2022.

RESULTS AND DISCUSSION

Full Sample Results

Table 3 below displays the APR for the B&H strategy for Bitcoin and the 10 alt coins from January 1, 2021, to December 31, 2022. The CTTRs issued a maximum of three to four purchasing and selling signals for each coin and token during the research period. For example, the Cardano token gained 94.90% from the first CTTRs purchase, lost -26.46% in the second, and lost -23.43% in the third purchase. This study also employed the BTD strategy in our CTTRs rule. Specifically, when the CTTRs reach the first buying signal, we will invest 40% of the initial capital of

USD100. For example, the first 40% purchase of Ethereum yielded 86.02%. When the price dropped further, indicating a second purchase signal, we purchased the remaining 60% of the initial capital, resulting in a total return of 157.74% for Ethereum on the second purchase for the first buy.

Table 3 shows that the CTTRs can outperform the B&H strategy in 5 of 11 coin and tokens, while the B&H strategy beats the CTTRs in the Binance, Avalanche, and Vechain tokens. Moreover, the CTTRs with a stop-order strategy incur less loss than the B&H strategy in Chainlink, Stellar, and Ethereum Classic. Evidently, our study demonstrates the potential of CTTRs in cryptocurrency trading, particularly when combined with the BTD strategy.

Table 3 APR for alt coins

Strategy	Bitcoin	Ethereum	Binance	Cardano	Avalanche	Chainlink
B&H	-43.60	64.63	550.67	40.38	197.83	-53.79
CTTRs 1st buy 40%	79.89	86.02	149.33	N/A	N/A	-17.47
CTTRs 1st buy 60%	28.74	157.74	38.47	N/A	N/A	N/A
CTTRs 1st buy 100%	N/A	N/A	N/A	94.90	-27.69	N/A
Total CTTRs PNL	49.20	129.05	82.81	94.90	-27.69	-6.99
CTTRs 2nd buy 40%	-27.64	-18.22	-31.12	N/A	N/A	N/A
CTTRs 2nd buy 60%	-22.20	N/A	19.19	N/A	N/A	N/A
CTTRs 2nd buy 100%	N/A	N/A	N/A	-26.46	-22.72	N/A
Total CTTRs PNL	-24.38	-7.29	-11.00	-26.46	-22.72	N/A
CTTRs 3rd buy 40%	N/A	N/A	N/A	N/A	N/A	N/A
CTTRs 3rd buy 60%	N/A	N/A	N/A	N/A	N/A	N/A
CTTRs 3rd buy 100%	N/A	N/A	N/A	-23.43	N/A	N/A
Total CTTRs PNL	N/A	N/A	N/A	-23.43	N/A	N/A

Note: Assume only USD100 is invested in each coin and tokens. The total PNL profit and loss is calculated with 0.4 to multiply the APR for buying 40% and 0.6 to multiply the APR for buying 60% to get the 100.

Table 3 Cont.

Strategy	Stellar	Algorand	E.Classic	Vechain	Tezos
B&H	-45.18	-57.49	173.10	72.90	-63.99
CTTRs 1st buy 40%	-24.38	N/A	-24.71	-28.05	-25.99
CTTRs 1st buy 60%	N/A	N/A	N/A	-43.44	173.78
CTTRs 1st buy 100%	N/A	137.36	N/A	N/A	N/A
Total CTTRs PNL	-9.75	137.36	-9.88	-37.29	93.87
CTTRs 2nd buy 40%	N/A	-26.28	N/A	N/A	-31.95
CTTRs 2nd buy 60%	N/A	-26.07	N/A	N/A	-21.42
CTTRs 2nd buy 100%	N/A	N/A	N/A	N/A	N/A
Total CTTRs PNL	N/A	-26.15	N/A	N/A	-25.63
CTTRs 3rd buy 40%	N/A	-22.16	N/A	N/A	N/A
CTTRs 3rd buy 60%	N/A	N/A	N/A	N/A	N/A
CTTRs 3rd buy 100%	N/A	N/A	N/A	N/A	N/A
Total CTTRs PNL	N/A	-8.86	N/A	N/A	N/A

Note: Assume only USD100 is invested in each coin and tokens. The total PNL profit and loss is calculated with 0.4 to multiply the APR for buying 40% and 0.6 to multiply the APR for buying 60% to get the 100.

Table 4 Bitcoin and 10 alt coins buying, price selling price, and date

No	Types	Strategy	Buying Price	Buying Date	Selling price	Selling Date	APR
1	Bitcoin	Buy and Hold	29331.69	2021-01-01T00:00:00Z	16542.40	2022-12-31T00:00:00Z	-43.60
		Complex Technical trading Rules 1st buy 40%	36690.09	2021-05-19T00:00:00Z	66001.41	2021-10-20T00:00:00Z	79.89
		Complex Technical trading Rules 1st buy 60%	35600.16	2021-06-20T00:00:00Z	45832.01	2022-01-04T00:00:00Z	28.74
		Complex Technical trading Rules 2nd buy 40%	41566.48	2022-01-07T00:00:00Z	30076.31	2022-05-09T00:00:00Z	-27.64
		Complex Technical trading Rules 2nd buy 60%	29029.75	2022-05-12T00:00:00Z	22583.72	2022-06-15T00:00:00Z	-22.20
2	Ethereum	Buy and Hold	728.91	2021-01-01T00:00:00Z	1196.13	2022-12-31T00:00:00Z	64.63
		Complex Technical trading Rules 40% 1st sell	1786.03	2021-07-20T00:00:00Z	3322.32	2021-08-13T00:00:00Z	86.02
		Complex Technical trading Rules 60% 1st sell	1786.03	2021-07-20T00:00:00Z	4603.35	2021-11-03T00:00:00Z	157.74
		Complex Technical trading Rules 40% 2nd buy	3080.95	2022-01-08T00:00:00Z	2519.71	2022-05-08T00:00:00Z	-18.22

Table 4 Cont.

No	Types	Strategy	Buying Price	Buying Date	Selling price	Selling Date	APR
3	Cardano	Buy and Hold	0.18	2021-01-01T00:00:00Z	0.25	2022-12-31T00:00:00Z	40.38
		Complex Technical trading Rules 100% 1st	1.12	2021-07-19T00:00:00Z	2.19	2021-08-14T00:00:00Z	94.90
		Complex Technical trading Rules 100% 2nd	1.27	2021-12-14T00:00:00Z	0.93	2022-02-20T00:00:00Z	-26.46
		Complex Technical trading Rules 100% 3rd	0.47	2022-05-12T00:00:00Z	0.36	2022-10-18T00:00:00Z	-23.43
4	Binance	Buy and Hold	37.78	2021-01-01T00:00:00Z	246.30	2022-12-31T00:00:00Z	550.67
		Complex Technical trading Rules 40% 1st buy	262.10	2021-06-22T00:00:00Z	653.50	2021-11-08T00:00:00Z	149.33
		Complex Technical trading Rules 60% 1st buy	342.39	2021-08-06T00:00:00Z	474.10	2022-01-05T00:00:00Z	38.47
		Complex Technical trading Rules 40% 2nd buy	429.90	2022-01-08T00:00:00Z	296.10	2022-05-09T00:00:00Z	-31.12
		Complex Technical trading Rules 60% 2nd buy	271.50	2022-05-11T00:00:00Z	323.60	2022-08-11T00:00:00Z	19.19
5	Avalanche	Buy and Hold	3.65	2021-01-01T00:00:00Z	10.90	2022-12-31T00:00:00Z	197.83
		Complex Technical trading Rules 1st buy 100%	56.98	2022-04-30T00:00:00Z	41.20	2022-05-09T00:00:00Z	-27.69
		Complex Technical trading Rules 2nd buy 100%	30.32	2022-05-12T00:00:00Z	23.43	2022-05-26T00:00:00Z	-22.72
6	Chainlink	Buy and Hold	11.85	2021-01-01T00:00:00Z	5.58	2022-12-31T00:00:00Z	-53.79
		Complex Technical trading Rules 1st buy 40%	26.23	2021-05-19T00:00:00Z	21.65	2021-06-20T00:00:00Z	-17.47
7	Stellar	Buy and Hold	0.13	2021-01-01T00:00:00Z	0.07	2022-12-31T00:00:00Z	-45.18
		Complex Technical trading Rules 1st 40%	0.24	2021-07-16T00:00:00Z	0.18	2022-04-29T00:00:00Z	-24.38
8	Algorand	Buy and Hold	0.40	2021-01-01T00:00:00Z	0.17	2022-12-31T00:00:00Z	-57.49
		Complex Technical trading Rules 1st 100%	0.74	2021-06-22T00:00:00Z	1.77	2021-10-10T00:00:00Z	137.36
		Complex Technical trading Rules 2nd 40%	0.95	2022-01-22T00:00:00Z	0.70	2022-03-11T00:00:00Z	-26.28
		Complex Technical trading Rules 2nd 60%	0.78	2022-02-24T00:00:00Z	0.57	2022-05-09T00:00:00Z	-26.07
		Complex Technical trading Rules 3rd 40%	0.45	2022-05-11T00:00:00Z	0.35	2022-06-11T00:00:00Z	-22.16
9	Ethereum Classic	Buy and Hold	5.69	2021-01-01T00:00:00Z	15.69	2022-12-31T00:00:00Z	173.10
		Complex Technical trading Rules 1st 40%	24.20	2022-01-22T00:00:00Z	18.22	2022-06-11T00:00:00Z	-24.71
10	Vechain	Buy and Hold	0.02	2021-01-01T00:00:00Z	0.02	2022-12-31T00:00:00Z	72.90
		Complex Technical trading Rules 40% 1st buy	0.07	2021-06-22T00:00:00Z	0.05	2022-01-22T00:00:00Z	-28.05
		Complex Technical trading Rules 60% 1st buy	0.05	2022-01-22T00:00:00Z	0.03	2022-05-18T00:00:00Z	-43.44
11	Tezos	Buy and Hold	2.01	2021-01-01T00:00:00Z	0.72	2022-12-31T00:00:00Z	-63.99
		Complex Technical trading Rules 40% 1st buy	2.91	2021-05-23T00:00:00Z	2.15	2021-07-20T00:00:00Z	-25.99
		Complex Technical trading Rules 60% 1st buy	2.15	2021-07-20T00:00:00Z	5.89	2021-08-29T00:00:00Z	173.78
		Complex Technical trading Rules 40% 2nd buy	2.96	2022-01-22T00:00:00Z	2.01	2022-05-09T00:00:00Z	-31.95
		Complex Technical trading Rules 60% 2nd buy	1.77	2022-05-13T00:00:00Z	1.39	2022-06-17T00:00:00Z	-21.42

Table 4 above presents a comprehensive comparison of the buying and selling dates, buying and selling prices, and the Annual Percentage Rate (APR) performance for Bitcoin and alt coins. This comparison covers both the B&H strategy and the CTTRs across the period from January 1, 2021, to December 31, 2022. The table facilitates the verification of data presented in other tables for future researchers. Specifically, the inclusion of the buying and selling dates and prices supports the replication and validation of the results reported in this paper and provides clarity on the implementation of the CTTRs strategy as analysed in this study.

Table 5 below displays the Sharpe Ratios of the single-CTTRs and B&H strategies applied to the daily Bitcoin return and 10 alt coins from January 1, 2021, to December 31, 2022. Our analysis indicates that a positive difference between the computed values of the CTTRs Sharpe Ratio and the B&H Sharpe Ratio typically indicates a profitable trade, while a negative value signifies a loss in trade. The highest B&H Sharpe Ratio number of -0.1185 was recorded for Avalanche. The difference between the Sharp Ratio of CTTRs and B&H strategy is also calculated. For instance, the Cardano first buy 100% CTTRs Sharpe Ratio is at 0.3045, indicating a difference from the B&H strategy benchmark of 0.4776. The associated p-value is 0.0203, indicating that this difference is statistically significant. Table 5 shows that CTTRs only shows statistically significant differences from the B&H strategy in 2 of 29 trades.

Table 5: Sharpe and p-value for Bitcoin and 10 alt coins

Trading Rules	Number of trades	Purchases	Complex Technical Trading Rules				
			Sharpe Ratio		Difference		
			CTTRs	B&H	from B&H	*p-value*	APR
Bitcoin	1	1st buy 40%	-0.1763	-0.2998	0.1236	0.28185	79.8900
	2	1st buy 60%	-0.2713		0.0285	0.40208	28.7400
	3	2nd buy 40%	-0.3724		-0.0726	0.68365	-27.6400
	4	2nd buy 60%	-0.4574		-0.1576	0.15173	-22.20
Ethereum	5	1st buy 40%	0.3444	-0.1938	0.5382	0.0620	86.0170
	6	1st buy 60%	-0.0455		0.1483	0.1759	157.7420
	7	2nd buy 40%	-0.3318		-0.1380	0.4820	-18.2165
Binance	8	1st buy 40%	-0.1007	-0.1377	0.0369	0.5781	149.3323
	9	1st buy 60%	-0.1991		-0.0614	0.8902	38.4678
	10	2nd buy 40%	-0.3286		-0.1910	0.3526	-31.1235
	11	2nd buy 60%	-0.2190		-0.0813	0.9489	19.1897
Cardano	12	1st buy 100%	0.3045	-0.1731	0.4776	0.0203	94.9042
	13	2nd buy 100%	-0.3222		-0.1490	0.3661	-26.4613
	14	3rd buy 100%	-0.2724		-0.0993	0.5411	-23.4312
Avalanche	15	1st buy 100%	-0.3695	-0.1185	-0.2510	0.2181	-27.6939
	16	2nd buy 100%	-0.3921		-0.2736	0.1996	-22.7243
Chainlink	17	1st buy 40%	-0.2075	-0.2090	0.0015	0.1719	-17.4667
Stellar	18	1st buy 40%	-0.2554	-0.1987	-0.0567	0.9356	-24.3823
Algorand	19	1st buy 100%	-0.0435	-0.1835	0.1400	0.2492	137.3588
	20	2nd buy 40%	-0.4079		-0.2245	0.5354	-26.2771
	21	2nd buy 60%	-0.2632		-0.0797	0.6493	-26.0679
	22	3rd buy 40%	-0.3883		-0.2049	0.5328	-22.1581
Ethereum Classic	23	1st buy 40%	-0.2326	-0.1338	-0.0988	0.4876	-24.7107
Vechain	24	1st buy 40%	-0.2089	-0.1439	-0.0650	0.7897	-28.0518
	25	1st buy 60%	-0.2307		-0.0868	0.5331	-43.4437
Tezos	26	1st buy 40%	-0.2083	-0.1839	-0.0243	0.5531	-25.9950
	27	1st buy 60%	0.1720		0.3559	0.0438	173.7752
	28	2nd buy 40%	-0.2737		-0.0898	0.7508	-31.9473
	29	2nd buy 60%	-0.2814		-0.0975	0.4547	-21.4245

Table 5 above suggests that the Sharpe Ratio is correct to indicate that a higher number means a higher return when the Sharpe Ratio number of CTTRs and B&H strategy difference is positive. Profit cannot be made when these differences have a negative value. For instance, Avalanche exhibits a difference in the Sharpe Ratios between CTTRs and B&H of -0.2736, suggesting a loss trade of -22.7243 in APR. We observe that, when the trade exhibits negative Sharpe ratio differences, indicating losses in trade, then the APR is also negative. There are few trades with positive Sharpe Ratio differences resulting in profitable trade with APR averaging above 100. In this study, Tezos, Ethereum, and Binance tokens exhibit the most profitable options. All of these tokens have a different positive Sharpe Ratio number.

Table 6 compares the performance of the B&H strategy with that of the CTTRs across different cryptocurrencies for the period from January 1, 2021, to December 31, 2022. The table presents the annual percentage rate (APR) results for Bitcoin and the 10 alt coins, providing a detailed analysis of profitability under both trading strategies.

The data showcases that CTTRs has outperformed the B&H strategy in several instances, particularly in highly volatile market environments. This suggests that CTTRs' dynamic and responsive approach to market changes can capitalize on price fluctuations more effectively than the more passive B&H strategy. For instance, the APR for CTTRs in Bitcoin's first buy 40% is 79.89, indicating a significantly higher profitability compared to B&H, which underscores the potential of active trading strategies in maximizing returns in fluctuating markets. However, it is important to note that our analysis reveals only 10 profitable CTTRs token trades. Many trades using the CTTRs resulted in losses, as shown in Table 6. In our study, it is difficult to conclude that applying this version of the CTTRs can surely trade with return.

Table 6 APR Ranking for Bitcoin and 10 alt coins

Trading Rules	Number of trades	Purchases	APR
Tezos	1	1st buy 60%	173.78
Ethereum	2	1st buy 60%	157.74
Binance	3	1st buy 40%	149.33
Algorand	4	1st buy 100%	137.36
Cardano	5	1st buy 100%	94.90
Ethereum	6	1st buy 40%	86.02
Bitcoin	7	1st buy 40%	79.89
Binance	8	1st buy 60%	38.47
Bitcoin	9	1st buy 60%	28.74
Binance	10	2nd buy 60%	19.19
Chainlink	11	1st buy 40%	-17.47
Ethereum	12	2nd buy 40%	-18.22
Tezos	13	2nd buy 60%	-21.42
Algorand	14	3rd buy 40%	-22.16
Bitcoin	15	2nd buy 60%	-22.20
Avalanche	16	2nd buy 100%	-22.72
Cardano	17	3rd buy 100%	-23.43
Stellar	18	1st buy 40%	-24.38
Ethereum Classic	19	1st buy 40%	-24.71
Tezos	20	1st buy 40%	-25.99
Algorand	21	2nd buy 60%	-26.07
Algorand	22	2nd buy 40%	-26.28
Cardano	23	2nd buy 100%	-26.46
Bitcoin	24	2nd buy 40%	-27.64
Avalanche	25	1st buy 100%	-27.69
Vechain	26	1st buy 40%	-28.05
Binance	27	2nd buy 40%	-31.12
Tezos	28	2nd buy 40%	-31.95
Vechain	29	1st buy 60%	-43.44

CTTRs enable traders and investors to trade with logic rather than greed and fear, potentially leading to profitable trades or investments. Many unique challenges and risks are associated with the cryptocurrency market, as cryptocurrencies are inherently volatile and can fluctuate significantly in a short period, making it quite impossible to gauge and predict market movements. The results of this study suggest combining the US market's strong market tailwind in the Nasdaq indices with the CTTRs to provide a valuable strategy for investors and traders in navigating the cryptocurrency market's volatility. However, this strategy works in the absence of a strong market headwind in the US equity market. When CTTRs is paired with a strong market tailwind, traders and investors can make more profitable investment decisions with confidence. This study focuses mainly on comparing the CTTRs and B&H strategy usage, and it does not include a discussion of a strong market tailwind or strong market headwind.

CONCLUSIONS

This study examines the profitability optimization of the cryptocurrency market through a comparative analysis between CTTRs and the B&H strategy. We demonstrate that applying CTTRs can result in profits that exceed those of the B&H strategy for the full sample period, even in highly volatile markets such as cryptocurrency. Our study places the advantages of CTTRs over the more commonly employed STTRs, which can generate returns and has proven useful for traders and investors in making informed decisions. Our results show that CTTRs successfully generates returns for Bitcoin, Ethereum, Cardano, Algorand, and Tezos, ranging from 79.89% to 173.78%. However, CTTRs is unable to defeat the weak form of EMH, with only two trades being statistically significant, i.e. Cardano and Tezos, while the rest are not statistically significant, despite generating returns in some trades.

The CTTRs employed in this study is unable to predict the future price movements of Bitcoin and alt coins, though it can yield better returns than the B&H strategy. Due to the limited trade with the statistically significant returns from CTTRs, this outcome lends support to the EMH, which posits that only FA and TA can surpass the weak form of market efficiency, as proposed by Fama (1970).

This study contributes to the existing literature on technical trading strategies by demonstrating the improvement in CTTRs portfolio returns, with some exceeding 100% in APR, compared to previous studies that have focused on STTRs in Bitcoin and other cryptocurrencies (Gerritsen et al., 2020; Ahmed et al., 2020). Overall, this study provides valuable insights into the effectiveness of CTTRs in cryptocurrency trading and contributes to the ongoing debate on the validity of the weak-form EMH in the cryptocurrency market.

Meanwhile, Bitcoin and alt coins exhibit a correlation in their price movements during the study period, and the study reveals that they are not fundamentally different in their price action. When applying other types of CTTRs to the cryptocurrency market, further research is necessary to determine if any differences exist between other categories of cryptocurrencies. The study also highlights the potential of other CTTRs by combining popular STTRs as one CTTRs to generate profits in the cryptocurrency market. Future research can focus on exploring other CTTRs in the 157 categories of cryptocurrencies when evaluating the effectiveness of these trading strategies.

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